

University of Canterbury

Measuring the exposure to Obesogenic Environments among New Zealand School Children

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Abstract

The prevalence of obesity has increased greatly in the last 30 years. Intensified urban landscapes have created environments that facilitate rising obesity rates. The level of unhealthy food consumption and physical activity accessibility has become imbalanced within the built and social environments of individuals. The term obesogenic environment has been used to describe the increased exposure to obesity, based on the characteristics of the surrounding environment. Previous academic literature has attempted to measure the contribution of obesogenic environment exposure to obesity health outcomes. The key aim of this research is to measure the correlation between obesogenic environments and BMI outcomes of New Zealand school children aged 5-14. Part 1 of this research method considered all children aged 5-14 sampled in the New Zealand Health Survey (NZHS) 2013/2014. Linear regression analysis was used to determine the correlation between BMI and selected NZHS participant responses; the key analysis in part 1 was the correlation between BMI and participants mode of transport to and from school. Part 2 of this research method focused on the New Zealand city of Hamilton. The research method used NZHS data to measure participant exposure to obesogenic environments based on the health responses given by participants. Geospatial network analysis was used to determine the NZHS participant's home, route and school environments. Obesogenic environment exposure was defined by the Hamilton food and physical environment attributes contained within euclidean buffer zones created around the participant's home, route and school environment. Linear regression analysis was then used to determine the geospatial correlation between the participant's environment exposure and BMI outcomes. The results of this research method suggest that participant's exposure to obesogenic environments did not contribute to obesity health outcomes, based on the lack of statistical evidence provided by the linear regression analysis.

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List of abbreviations

Body Mass Index (BMI)

Census Area Unit (CAU)

Centres for Disease and Control and Prevention (CDC)

Geographic Information Systems (GIS)

Meshblock (MB)

Ministry of Health (MOT)

National Health Interview Survey (NHIS)

New Zealand Health Survey (NZHS)

Population Weighted Centroids (PWC)

Waikato District Council (WDC)

World Health Organisation (WHO)

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Chapter 1 – Introduction

Obesity is one of the most severe public health issues of the modern day. The growing prevalence of obesity has increased dramatically in the last few decades, leading to what many have now labelled a public health epidemic. Obesity prevalence can be understood by an imbalance created within the modern day lifestyle; these imbalances is manifested within significant changes to an individual's food and physical environments, (Williams *et al.*, 2013). The access and availability of food sources in a community environment has been drastically altered, with unhealthy, low nutritional value foods becoming more regularly incorporated into a consumers diet, (Bowman *et al.*, 2004). Adversely, individuals are becoming less physically active. Urban spaces are dominated by forms of passive transport (primarily automotive), making active transport alternatives both inaccessible and unappealing to individuals, (Grow *et al.*, 2008). Individuals are become less physically active as a result. These imbalances created between these two aforementioned factors is recognized as one of the key drivers in the global increase in obesity rates. The health consequences of obesity are wide spreading. Obesity has been described by Frühbeck and Yumuk (2014) as a 'gateway' disease, acting to increase the risk to medical conditions such as diabetes, hypertension and coronary heart disease. Obesity can also profoundly impact facets of social health, such as self-esteem and self-confidence, (Wilson *et al.*, 2006). The global cost of obesity presents an enormous economic challenge to the public health sector. The global medical cost of obesity is estimated to be between \$147 billion and \$210 billion per year, (Chenoweth & Associates, 2009). The diverse health consequences and high cost make the obesity epidemic an important public health concern in the future.

1.2 Obesogenic environments

There is a growing emergence in academic literature suggesting the surrounding built and social environment contributes to health outcomes, both at an individual and community level, (Ebbeling *et al.*, 2002a). This notion is reflected within obesity outcomes. Previous research has identified areas within a population that have an increased exposure to obesity based on the characteristics of the surrounding environment. The term obesogenic environments was coined by Swinburn *et al.* (1999), describing this concept as “an environment that promotes gaining weight and one that is not conducive to weight loss within the home or workplace.” An obesogenic environment is the embodiment of the imbalance between food access and physical activity referenced previously. Obesogenic environments are typically defined by a highly imbalanced food and physical environment. This describes areas with access to a high number of unhealthy food sources, and low access to mediums of physical exercise. Mapping and measuring obesogenic environments has been a key challenge within epidemiology research. GIS method based approaches have attempted to identify geographic areas that display obesogenic symptoms, suggesting that residents of these areas are predisposed in their exposure to obesity.

1.3 Obesity in New Zealand

New Zealand is recognized by the OECD to have the third highest rate of obesity globally, (OECD, 2014). The rate of childhood obesity has been one of the key concerns within the New Zealand obesity epidemic. Obesity in New Zealand has found to be linked closely to inequality. Individuals who live in highly deprived areas are 44% more likely to be obese, (Ministry of Health, 2015). Pacific Island and Maori ethnic groups are disproportionately affected by obesity, 66.8% and 48% respectively recognized as obese by the NZHS, (NZHS, 2013). Childhood obesity rates

in New Zealand are one of the major problems in the obesity epidemic. Approximately one in three New Zealand children aged 2-14 are overweight; 11% of these children are obese, (OECD, 2014). The majority of children represented within the previous statistic are school children. Health intervention in obesity has been a source of debate within the context of New Zealand public health. The New Zealand government has called for the introduction of a health target to reduce obesity rates nationally. Despite this objective, there is currently no meaningful health intervention directly targeting obesity at a national scale in New Zealand.

1.4 Research Purpose

The purpose of this research was to establish a connection between exposure to obesogenic environments and obesity outcomes of New Zealand school children. This thesis will use data from NZHS 2013/2014 edition to determine how BMI outcomes of New Zealand children aged 5-14 are influenced by environmental exposure to obesity at a neighbourhood level. This thesis will focus on obesity outcomes in New Zealand on two different scales. Part 1 of this research method is a nationwide analysis, which includes 2404 children aged 5-14 from the NZHS. The nationwide analysis will focus on the connection between BMI and the health responses given by the NZHS participants, primarily social deprivation, ethnicity and mode of transport. Part 2 of this research method focuses on the New Zealand city of Hamilton. A geospatial analysis was conducted on 70 NZHS children aged 5-14. GIS was used to map and measure participants' exposure to obesogenic environments in Hamilton, based on the food and physical characteristics of the surrounding area. Exposure was measured by the participant's home, route and school environment, which was compared to BMI status. This determined if exposure to obesogenic environments contributed to obesity outcomes among Hamilton school children.

1.2 Research Aims and Objectives

The key aim of this research is to examine the relationship between exposure to obesogenic environments and obesity outcomes among children.

There are three key objective of this research:

- 1) Undertake a national analysis of the childhood obesity using the NZHS 2013/2014.
- 2) Identify the exposure of school children to obesity based on the characteristics of the food and physical environments in Hamilton
- 3) To relate obesogenic environments and health outcomes among Hamilton children

1.3 Thesis Structure

Chapter 1 of this research project introduces the reader to the key aims and objectives of this research project.

Chapter 2 introduces the wider context of obesity on a global scale. This chapter will introduce the reader to the bio medical and social health context of obesity, and explain how the modern development has led to an increase in the prevalence of obesity.

Chapter 3 will introduce the reader to the concept of obesogenic environments. The development of urban inequalities will be discussed, identifying how this process has influenced the creation of obesogenic environments. This chapter will also review how previous academic literature has mapped and measured obesogenic environments, helping to shape the research method for this thesis.

Chapter 4 will focus on the context of obesity in New Zealand, outlining the current demographic groupings in New Zealand that are adversely affected by obesity, (particularly social deprivation and ethnicity). This chapter will also describe how the current response to obesity in New Zealand is being approached, both at community and nationwide levels.

Chapter 5 describes the methods used within this study. This chapter will discuss the data sources used in this research method, with particular reference to the privacy and safety of the selected NZHS participants. The geospatial method to measure the food and physical environments in Hamilton city will be clearly outlined, explaining how the GIS method created, mapped and measured obesogenic environments in Hamilton.

Chapter 6 will report the results of the part 1 and part 2 method analysis. Part 1 results will explain the connection between BMI and social deprivation, ethnicity and mode of transport using linear

regression analysis models. Part 2 results will explain the connection between environment exposure to obesity determined by BMI and social indicators of obesity. Mode of transport and nutritional intake are variables from the NZHS. They will be used to determine their influence on a participant's environment exposure. This research will refer closely to tables and figures from the analysis models to justify the findings.

Chapter 7 will discuss the key findings from part 1 and part 2 of the analysis results. This chapter will compare the results from the nationwide and Hamilton geospatial analysis to better understand how patterns and trends manifest between the two different geographic focus areas. The future implications of the key findings will also be discussed in the context of New Zealand obesity, alluding to how specific findings should be considered in future health intervention strategies. This chapter will also outline the limitations of this research project, primarily within the mapping and measuring of obesogenic environments in the Hamilton geospatial analysis.

Chapter 2- childhood obesity

2.1 Chapter Summary

The key purpose of this chapter is to comprehensively define and explain how and why obesity has become one of the most important public health issues of the modern world. This will also address why obesity poses a significant health threat to children, both presently and in the future. This chapter will begin by defining obesity, and explain how the imbalance in both diet and lifestyle have been a key enabler behind obesity prevalence. The BMI weight measurement method will be explained and discussed, referring to both the positive and negative aspects of this calculation. The health consequence and cost of obesity will be thoroughly outlined, with close regard to previous literature. The last section will refer to previous case studies to determine how effective health intervention has been used to prevent obesity at the population level.

2.2 Introduction

The prevalence of obesity has been increasing within the developed and developing world over the last half century. Western countries especially have seen large increases in obesity rates. The USA has particularly seen a large increase in obesity rates, threatening to overtake smoking as the number one cause of preventable death in the United States, (Eckel and Committee, 2010). Similar trends have also been observed in United Kingdom (UK), (Deckelbaum and Williams, 2001). 65% of all males, and 56% of all females in the UK are currently overweight or obese, (Wilson *et al.*, 2006). If the current rate of obesity continues, it is estimated that 25% of all UK children will be obese by 2050, (Zaninotto and Britain, 2006). The USA has seen a 50% increase in the rates of childhood obesity in the past 30 years; one fifth of US children are now overweight and obese, (Gardner and Halweil, 2000). This trend has also been observed in New Zealand. A report by the

Ministry of Health (2015) showed one third of New Zealand children aged 5 to 14 years were overweight, 11% were obese. Childhood obesity has a detrimental effect on overall health. The key issue highlighted in public health research is the increasing likelihood of overweight and obese children continuing to be so as adults; this point will be explored within later in the chapter.

The forecasted increase in obesity levels globally makes it one of the most important issues in modern public health. Obesity was labelled as an epidemic by the World Health Organisation (WHO), who have included decreasing obesity rates as one of the WHO Millennium goals released in 2000. Obesity is defined by WHO (2015) as an “abnormal and excess accumulation of fat that leads to impairment in overall health.” Obesity represents an imbalance in energy input and output within the human body. Input refers to energy consumed through eating and drinking. Output refers the energy that is expended in order for humans to function, primarily through physical activity. When the amount of energy consumed is greater than amount expended, the energy not utilized is stored as fat cells. The excess built up for these fat cells leads to obesity. The imbalance between energy input and output can be primarily attributed to drastic changes in modern day lifestyle, (Wright and Aronne, 2012). The prevalence of obesity is linked to two key factors: an increasing availability of high density, low nutrition food sources and an increasingly inactive lifestyle, (Townshend and Lake, 2009). The changing nature of food availability and consumption is one of the fundamental drivers behind the increase in obesity. Drewnowski & Specter (2004) have noted that widening disparities between the cost of healthy and unhealthy food sources. This has been a key facilitator behind the available of highly energy dense food. These food sources, such as caloric beverages and fast food have become far more readily available and affordable, making these food types a cheap and easy source of energy. There has been a large increase in unhealthy food consumption among children. Unhealthy food sources, particularly fast food has

become a regular component of a child's diet, (Bowman *et al.*, 2004). A fast food driven diet poses serious health problems. Desa (2013) has stated that the lack of quality and diversity in the availability of food has led to the creation of malnutrition in an increasingly unhealthy diet. This issue has now become more globally relevant than hunger and undernourishment.

The second reason for increased obesity is linked to a gradually inactive lifestyle. Individuals are simply not as physically active day to day in contemporary living. A highly dynamic built environment (especially in large cities) works against access and exposure to everyday physical activity, (Humphrey, 2005). The modern day built environment allows people to move within an area using a myriad of inactive transport modes, such as cars and buses. This makes active forms of transport such as walking and cycling either unavailable or impractical, (Wright and Aronne, 2012). The modern day working environment is far less active, with a sharp increase in office and inside jobs, as opposed to jobs that require physical activity, (Tigbe *et al.*, 2011). With fewer opportunities of casual physical exercise, individuals are becoming less physically active. The imbalance between the two objectives discussed has catalysed environments that increase the risk to obesity exposure.

2.3 Health Related Consequences

There are a number of health related consequences that stem from childhood obesity. In the past, obesity has been referred to as a 'gateway disease'. The consequences of being obese have a number of direct and indirect effects upon a broad scale of health concerns, (Frühbeck and Yumuk, 2014). WHO (2015) state that one fifth of all global deaths are caused directly or indirectly by obesity. Some of the most common ailments include an increased chance of diabetes hypertension, dyslipidaemia, chronic inflammation, increased blood clotting tendency, (Deckelbaum and Williams, 2001). Kopelman (2007) states the risk of type 2 diabetes is increased by 90% if an

individual is overweight or obese. The influence of obesity on coronary heart disease has been a major focus in health research. The connection between obesity and coronary heart disease was previously seen as unsubstantiated. Research has now shown that BMI is directly independent on the likelihood of coronary heart disease, (Eckel and Committee, 2010). This connection is particularly evident among children. A study conducted by Freedman *et al* (2001) found that children who are obese are 77% more likely to suffer from coronary heart disease as an adult. This study also highlights that childhood obesity leads to severe health consequences in later life. An overweight or obese adolescence is 25% to 50% likely to also be so as an adult, (Must and Strauss, 1999). One of key causes for the transference of obesity from children to adult is a habituated unhealthy attitude towards food, (Krebs *et al.*, 2007). As childhood obesity rates increase in the future, the cost of childhood obesity will also increase. This is mainly due to the diverse negative health outcomes that obesity can lead to.

Obesity has adverse effects on an individual's social health. The prevalence of childhood obesity has led to changing attitude around what constitutes a healthy body image. A research paper by Ebbeling *et al* (2002) has noted that 'fat children' have historically been considered healthy, due to their resilience against undernourishment and infection. It is ironic that a body shape once considered to a healthy child, now is a body shape considered highly undesirable among children. The drastic change in the preserved 'healthy body image' represents just how serious the prevalence of obesity has become. Previous research has shown that overweight children (particularly those aged between 13 and 14) are more far more likely to have low self-esteem, (Strauss, 2000). The early stage of adolescence is a critical time for children to define their own self-worth. In this case, their self- worth is strongly linked to how they believe others perceive them. Self-image is a very important aspect of adolescences development. Social and cultural

mediums such as television and advertising place a strong emphasis on ‘thinness and fitness,’ (Strauss, 2002). This can prompt adolescents to believe that being overweight or obese is social unacceptable, which can be highly detrimental to a child’s self-confidence.

“There is no doubt that obesity is an undesirable state of existence for a child. It is even more undesirable for an adolescent, for whom even mild degrees of overweight may act as a damaging barrier in a society obsessed with slimness.”(Bruch, 1975, Pg91).

The health consequences of obesity are wide ranging. The high number of the negative health issues that are catalysed by obesity is troubling, particularly when we consider that obesity rates are continuously rising globally.

2.4 Body Mass Index measurement

BMI is the most commonly used system to measure an individual’s weight status. BMI stands for Body Mass Index, and is a very simple method in which to determine whether a participant is at risk of being overweight or obese. BMI essentially measures adiposity, which refers to an individual’s level of ‘Fatness or thinness.’ Participants are required to submit their height and mass in order to gauge their relative weight under the BMI system. The equation to calculate BMI is listed below.

$$\text{BMI} = \frac{\text{Weight (kg)}}{\text{Height}^2 (\text{m}^2)}$$

(Physiologyweb, 2014)

An individual with a normal BMI should be between 18.50 and 24.99. An individual between 25 and 29.99 is classified as overweight: an individual rated $30 \leq$ is classified as obese. A chart of BMI levels is shown in Appendix 1. This chart indicates the BMI classification scale for weight and height.

There are advantages and disadvantages to using the BMI system. The primary advantage is the simplicity of the system. Individuals are only required to submit two attributes (height and mass) in order to calculate BMI. This makes the system quick and easy for participants. The BMI system can be used on both males and females, as well as all age groups. This makes BMI a standard form of measure, which is very useful for large scale research. The application for BMI in social science research has been widespread and diverse, especially within the research field of health geography. Virtually all wide scale health studies use the BMI method weight status. The 2013/2014 NZHS, which is heavily utilized within this study used the BMI method, (NZHS 2013).

The disadvantage to using BMI is the relative inaccuracy of the system. As has been stated, BMI is a very quick and simple measure of adiposity. However evidence suggests that certain body types are disproportionately represented through the BMI method. BMI is unable to distinguish between fat, muscle and bone, (Burkhauser and Cawley 2008). Muscle is far more dense than fat, therefore individuals with a muscular build can be incorrectly classified under the BMI system. This is particular prominent among elite athletes, many of whom have a high BMI due to their mass, when in reality their mass is simply a result of muscle, not fat. A case study into NFL (National League Football) player Jermaine Mayberry is a good example of the issues of BMI and body type. Mayberry weights 148 kg and stands at 1.94m, (Prentice and Jebb 2001). These attributes would give Mayberry a BMI of 39.7, which classifies him as morbidly obese. However the BMI system does not take in account the high level muscle content within Mayberry's

physique, which largely distorts the results of the BMI test. BMI does not distinguish between age, sex and ethnicity; all of which are assumed to be independently classified in the parameters of the BMI method, (Gallagher, Visser et al. 1996). This is particularly evident in the relationship between BMI and age. Previous research indicates that adult participants with a similar BMI to a child have a greater fat composition within their bodies, (Prentice and Jebb 2001). This suggests that the BMI test fails to account for changing fat content in regards to age. The body shape of adult is far more likely to vary than that of a child, which makes it difficult to accurately determine their adiposity under the BMI system. It was been suggested by previous researchers that BMI should not be used for individual analysis. This is mainly due the lack of accountability for variables such as race, age and sex. There are a number of opposing methods such as mid-arm circumference and calf circumference tests, (Tsai, Lai et al. 2012). Although these methods are far more accurate than BMI, they require a greater amount of time and resources when compared to the simplicity of the BMI test in determining obesity.

BMI will be the measure used within this study. The information for this study is being provided by the New Zealand MOH, who conducted the NZHS. BMI is the only indicator of adiposity provided within the NZHS, hence its inclusion in this study. The advantage to using BMI in this research project is simplicity of BMI method. This study is required to be completed within a year. Other methods to measure adiposity would be far more time consuming to collect, given the scale of the study. The BMI method provides quantitative outputs that are simple to analysis, given the time parameters of the study. Children are physically less developed than adults, meaning that the potential variance in body shape is less emphasised.

2.5 Cost of Childhood Obesity

The economic and social cost of childhood obesity is a serious concern for public health. As was established above, there are a number adverse health consequences that result from overweight and obesity. As obesity rates continue to increase globally, the cost of treatment increases accordingly. These costs are not solely medically related. They also have severe economic and social implications if obesity rates continue to increase in the future. The methods for calculating the true cost burden of obesity has been a source of debate within the academic context of medical and economic research. An American study conducted by Chenoweth & Associates (2009) estimated the globally medical cost of obesity at \$147 billion and \$210 billion per year, which accounted by approximately 10% of annual medical spending. This figure has been quoted in a number of studies since its commission. However its current validity should be questioned. The figures are highly inaccurate, with \$33 billion being the margin of error in the studies estimate. This figures are also dated. This data used in this study was from 2006, which in context of obesity's increasing prevalence, can safely be considered outdated. The true medical cost of obesity globally is unclear; the key reasons being the wide array of negative health outcome make it hard to calculate. The economic and social cost of obesity has been an area of keen focus in a number of previous academic studies. Evaluating the economic cost of obesity is an important step for health services, primarily in regards to future health intervention.

Research by Withrow & Alter (2011) undertook a systematic review of all research papers between the 1990 and 2009 relating to the economic cost of obesity. The study found, (based on the 32 research papers reviewed) that 0.7% and 2.8% of total healthcare expenditure was accounted for by obesity; this research also found the individuals cost of obesity is 30% per patient compared to individuals with normal weight. While this research does provide interesting insights into the

individual cost of obesity, the recommendations acknowledge the necessity for more research into the cost of obesity at population level. This is in order to better facilitate obesity intervention and prevention. A similar research method was taken by Dee *et al* (2014), who set out to assess both the direct and indirect cost of obesity using a literature review method. This study finds that 54% to 59% of the total cost of obesity results from indirect economic costs, mainly as a result of losses in productivity due to illness, disability and morbidity. This suggests that the true cost of obesity may not immediately be apparent. The high indirect cost of obesity reflects the high number of indirect negative health outcomes that obesity can cause. The indirect consequences of obesity should also be considered carefully in future health planning and intervention, particularly in reference to healthcare spending.

While the high direct and indirect cost of obesity have been highlighted in literature reviews and studies, there has been little attempt to identify what these specific costs are. The direct medical costs of obesity, such as increased likelihood of hypertension, diabetes and CHD are all well founded within obesity research. However, a study by Wolf and Colditz (1998) has suggested that there are a number of independent costs, such as work lost days, restricted activities and bed days, all of which are negatively impacted by obesity. This study used data from the 1988 and 1994 National Health Interview Survey (NHIS) to assess the connection between these indirect costs of obesity and BMI status. Between 1988 and 1994, individuals with a BMI of ≥ 30 saw a 50% increase in work lost days, 28% increase in bed days and an 88% increase in physician visits as a result of obesity.

In the context of this study, it is important to understand the existence of indirect costs of obesity. This research attempts to identify some of the causal factors that drive obesity in New Zealand. Much like the costs of obesity, these factors impact the rate of obesity in New Zealand both directly

and indirectly. Epidemiology studies generally focus on health at a population, rather than an individual basis. The key focus in this study is to understand how the surrounding environment influences childhood obesity. Any environmental factors that influence a child's exposure to obesity should be considered as an independent cause. It is important to understand the role that external indicators play in health outcomes, and move away from the thinking that obesity is simply a bi-product of individual inadequacy.

2.6 Obesity and Public Health Intervention

The increasing public health burden of obesity has led to increased pressure for public health intervention. Without meaningful and effective public health intervention, the prevalence will continue to increase, further fuelling the health costs and consequences of the obesity epidemic. The direct bio medical causes of obesity are well established: an imbalance between energy input and output, leading to excess body fat. Therefore a purely bio medical health intervention requires a correction of this imbalance by eating less and being more physically active. The effectiveness of such a simple health solution has been rejected by (Ebbeling *et al.*, 2002b). This research has referenced a study by the US National Institute of Health, stating that adults on weight loss programmes lose only 10% of their body mass. In addition, most adults regain the weight lost in the following five years, (Goodrick *et al.*, 1996). This study demonstrates that public health intervention addressing obesity at an individual level is ineffective. Also, it is not cost effective due to high rates of obesity. The majority of the previous public health interventions have targeted obesity at population level. The methods of obesity intervention have been varied, as is effectiveness in reducing obesity rates.

The bulk of previous academic literature has set out to review the effectiveness of health intervention strategies by systematically comparing the success that different policies have had

within a population. The majority of targeted health interventions for obesity can be categorized into two key focus areas: built environment intervention and social environment intervention. Both of these categories will be explained and summarised below.

2.6.1 Build Environment Intervention

The built environment is defined by Sarkis *et al.* (2012) as all buildings and living spaces that are created, or modified by people. The composition of the built environment is an important determinant in obesity, which can both facilitate and hinder healthy eating and physical activity, (Booth *et al.*, 2005). In short, the energy input versus energy output is largely determined by the built environment. Health interventions seek to modification of the built environment in order to facilitate a healthier lifestyle. Intervention within the built environment should specifically aim to reverse the obesogenic drivers that have enabled the prevalence of obesity, (Boyd A. Swinburn *et al.*, 2011). Increasing the access to physical activity has been a key area of focus in obesity intervention. The promotion of active recreational facilities and transportation are two aspects of this. The nutritional value of food sources in the built environment is another key focus of health intervention. The available of unhealthy food (both in a commercial and home environment) has become an increasingly relevant issue in the context of obesity, (Cummins and Macintyre, 2006). The food and physical aspects of the built environment and the impact on obesity will be further explored in the Chapter 4: obesogenic environments.

2.6.2 Social Environment Intervention

The social environment considers the social processes and interactions that influence an individual's lifestyle, (McNeill *et al.*, 2006). Health intervention within the social environment focused primarily on the modification of the behavioural characteristics and the social habits that drive obesity. One of the key aspects of obesity intervention has been education, a strategy that is

particularly applicable to children and adolescents. Research conducted by James *et al.* (2004) has identified the importance of education in regards to obesity prevention in virtually all of the fifteen studies systematically review. This study site how the education, both within the home and school environment helps to support a healthier lifestyle. A report by the New Zealand Health Strategy (2001) has cited the social influence of the media upon obesity rates; this study makes particularly note of soft drink manufacturers, who have been seen to specifically target children in their advertising.

Alternative social intervention strategies seek to utilize the capacity of internet to promote health and active living. The concept of E-Health (or internet medicine) has introduced in the early 2000s, and refers to the development and promotion of health through the median of the internet, (Eysenbach, 2001). Mackert *et al.* (2009) has recognized the potential of how e-health could be applied to in the context of obesity prevention. This study references the effectiveness of the internet as a median of communication, providing relevant health information in a more palatable form for 'low-health-literature' audiences, many of whom would be either unable or unwilling to access this information within an academic context.

Summary

This chapter has outlined the obesity health epidemic. The health related consequences of obesity are wide spread, having a particularly impact upon children. The economic and social cost of obesity are also continuing to increase. These costs cause a number of problem, both at a population and individual scale. The need for obesity intervention is critical if rates are to decrease in the future. It is important to understand how decisions and processes of the past have created the current economic and social climate that has led to an unheralded rates of obesity increase globally. The next chapter of this research project explore how social and economic inequalities

have led the current obesity epidemic. Recognizing the societal problems that facilitate obesity increase is the key to a well-considered and health consequence response.

Chapter 3 – Obesogenic Environments

This chapter will define the concept of an obesogenic environment, and explain how it has become such an important public health issue. I will explain how changes in the built environment have influenced the increasing rate of obesity globally. I will describe the context of urban inequalities and obesity by outlining a brief history of how urban inequalities have been created, and how they impact upon urban areas in the modern day.

This concept of obesogenic environments will explained by describing how the balance between the food and physical environments can determine obesity outcomes within neighbourhoods and communities. This chapter will also outline how GIS has been used to measure the food and physical environments, explaining how this research project will be contributing the previous literature on obesogenic environments.

3.1 Obesity and Inequality

“Any city however small, is in fact divided into two, one city of the poor, the other of the rich”. Plato. (427-347 B.C.). (Landau, 2008)

Urbanisation has become an influential process in the last half century. Since the beginning of the 20th century urban landscapes have been expanding, in regards to both area and population. The industrial revolution is seen as a key driver behind this process. This created economic and social opportunities within cities, leading to sharp population shift from rural to urban living. The rapid increase of urbanisation has created highly dynamic urban landscapes. One of the key characteristics is a highly dense population. The dense population creates a higher level of accessibility to basic necessities, such as food and water; it also created a large and readily available labour force, who have benefited from increased economic opportunities within urban landscapes, (Hobsbawm, 2010). However, as urban population continued to increase globally, the supply and demand of economic and social resources became imbalanced. As more and more individuals continued to migrate into urban areas, the resources that make urban living so attractive, such as employment and education opportunities become scarce, due to increased demand for such resources. As economic growth increases, the social stratification of urban living became divided and unequal, (Bartlett *et al.*, 2014). This inevitably leads to a widening gap between wealthy and poor within urban spaces. This concept is known as urban inequality.

Urban inequalities have been rising in the age of post modernity. Many academic sources have pointed to globalization as a key driver behind the increasing segregation in urban areas. The concept of globalisation is applicable within many different academic fields, such is the multi-lateral nature of this process. In regards to urbanisation, globalisation refers to an increase in

connectivity between global networks, both internal and external to urban landscapes. The term global network society has been used to describe this occurrence, (Castells, 2010). Growing urban inequalities have been a focus of much academic research over the past few decades. It is important to understand the different sorts of inequalities that arise within urban areas. Urban areas have been characterised as heterogeneous spatial patterns, (Haddad and Nedovic-Budic, 2006). These spatial patterns give an indication of both where urban inequalities manifest, and who is negatively affected. When urban areas are severely shaped by inequalities, the city can be thought of as internally divided between rich and poor: this occurrence has become known as the '*Dual City*' theory. The dual city hypothesis was a concept by Mollenkopf and Castells (1991) used in case study for New York. The dual city reference is intended to serve as a metaphor to show the growing social and economic disparities between certain demographics within New York. Castell and Mollenkopf described how the rapid influx of population and changing economic structure has led to the city being metaphorically divided into two halves. The first being vastly wealthy, with individuals enjoying positive economic and social benefits. Inverse to this is the second city; that is heavily effected by poverty, ill health and crime. Together these two metaphoric cities make up the two halves of the dual city hypothesis. The New York '*Dual city*' example is only one of a growing number world-wide. As urbanisation continues to increase population, inequalities will enviably development.

Increasing urban inequalities has been a factor in the increasing obesity prevalence. Chapter 3 references how the changing nature of the built environment has compounded obesity rates. Processes such as urban sprawl have created urban landscapes that lead to negative health outcomes, (Lopez and Hynes, 2006). Urban landscapes have become far more dependent on passive form of transportation, such as car and buses. As a result, the built environment

discourages forms of active transportation, such as walking and cycling. These environments are barriers to physical activity, discouraging individuals due to lack the of diversity and accessibility to neighbourhood facilities, (Centers for Disease Control and Prevention, 1999). Physical inactivity is a key contributor to obesity. This suggests that individuals who live in areas of physical inactivity are more exposed to obesity, based on the characteristics of the surrounding built environment, leading to the obesogenic environment concept.

3.2 Defining Obesogenic Environments

“Obesity is a normal response to an abnormal environment”,
(Weight Management Centre, 2010)

The term obesogenic environment is a relatively new concept within public health research. Obesogenic environments consider the influence the built environment has on the outcomes of obesity, (Booth *et al.*, 2005). It also represents a different form of analytical enquiry into the symptoms of obesity. It is more effective to understand obesity from an epidemiological health stance. This is far more cost effective than considering obesity on an individual case basis, (Horgen and Brownell, 2002). The interaction between the built and social environments that individuals are exposed to is critical in defining obesogenic environments. The built environment is defined by Sarkis. *et al* (2012) as all the buildings and living spaces that are created or modified by people. Understanding the changing built environment is the most important step to understanding how obesogenic environments are created. Weight Management Centre (2010) states that obesity is a normal response to an abnormal environment. The rapid intensification of the built environment (particularly within urban areas) has led to the promotion of an unhealthy lifestyle, which has been a key enabler in the prevalence of obesity. Urban intensification has created an imbalance between the food and physical aspects of the built environment. This in turn

has altered the way people interact with their surroundings. In order to understand how obesogenic environments are created, it is necessary to understand how the food and physical environments of a community can influence obesity outcomes.

3.3 Food Environment vs Physical Environment

The food and physical aspects of an area are the most important characteristics when identifying obesogenic environments. The connection between the food and physical components are symbiotic in nature. The balance between the two concepts defines an individual's exposure to obesogenic environments. The following section is a brief summary of what the food and physical aspects of an environment are, how they influence our association with the built environment, and how an imbalance between the two has led to an increase in obesity.

3.2.1 Food Environment

The food environment refers to geographic access of food sources (commercially and residentially) within a given community, (Health Canada, 2013). The food environment is an important factor in determining the types of food people consume. Accessibility is the key variable. People are more likely to purchase food from sources proximate to where they live; therefore areas that have a high concentration of unhealthy food options (such as takeaways and fast food outlets) are more likely to consume unhealthy food sources. The inaccessibility of healthy food sources is a typical characteristic of an obesogenic environment. The term toxic food environment has been used in previous literature to describe this. A toxic food environment typically contains inexpensive and convenient food sources, many of which are unhealthy, (Horgen and Brownell, 2002). Toxic food environments are also been referred to as 'Food Deserts'; these are deprived areas with limited access to food; predominately due to a lack of proximity and affordability, (Cummins, 2014). There are several different components to a neighbourhood food environment that influence the

risk of obesity. Sallis and Glanz (2009) have described three different levels of the neighbourhood food environment, each demonstrating how the food environment influences a specific facet of a community.

i) Home food environment

The home food environment is the availability of food sources within the family home. The term home is a highly complex and dynamic, mainly due to the large amount of internal and external controls that influence the home food environment, (Story *et al.*, 2008). The home food environment for children is highly reliant on parental influence. The availability of food (both within the home and from the surrounding food environment) is directly dependent on the child's parents or caregivers, (Bryant *et al.*, 2014). An American nationwide survey conducted by Guthrie *et al.* (2002) found that American children consume approximately two thirds of their daily calorie intake within the home food environment. Parents also are important in shaping their child's behaviour towards food. This idea will be explored later in the chapter. The home food environment is linked closely to the local community food environment. The food choices that consumers make reflects the food available within the local food environment. A home with a lack of access to healthy food will be less likely to consume healthy food choices. The socio economic status of the home environment has proven to be an important determinant of obesity. Healthy food choices are more expensive, providing difficulties for lower income families. Food options such as vegetables and fruit are either too expensive or inaccessible, (Story *et al.*, 2008). A research paper by Strauss and Knight (1999) concluded that children from lower income families have an increased risk of obesity; this research also suggested that children are more likely to suffer from obesity if their parents (specifically their mother) is also obese. This reinforces the importance of how unhealthy food behaviour learnt as a child contributes to obesity outcomes, in

both children and adults. This behaviour is strongly defined by parental influence, which is fundamental to the home food environment.

ii) Community food environment

This refers to the distribution, location and accessibility of food sources within a community environment, (Glanz *et.al.*, 2005). The range of food stores present within a community have a major effect on the eating habits of its residents. When the availability of healthy food sources, (such as supermarkets and greengrocers) are scarce within a community, residents are unable to easily access healthy food sources. This leads residents to consume more accessible, yet often unhealthy food sources. These sources typically have a low nutritional value, yet are relatively inexpensive for consumers, (JF Sallis and Glanz, 2009). This has previously been referenced as a toxic food environment, in which the availability of unhealthy food sources outweighs the healthy sources. The definition of what constitutes an unhealthy food source is not always clearly defined within academic literature. However in a broad sense, unhealthy food sources are foods containing high levels of calorie and fats and sugar; Brownell (2004) refers to the presence of fast food outlets as the most influential source of unhealthy food sources within the community food environment.

iii) School food environment

The school food environment is a highly influential factor in determining a child's eating behaviour, (Kubik *et al.*, 2003). Children spend the large amount of time at school, therefore a healthy (or unhealthy) school food environment is a key indicator of dietary behaviour, (Kubik *et al.*, 2005). The area surrounding schools has been a source of debate in the context of obesogenic environments. It is suggested that fast food outlets (such as dairies and takeaways) are disproportionately situated in close proximity to schools. No major study to date has found a

connection between childhood obesity and the surrounding school environment. However, it has been established that the built environment can have an inherent influence on a child's eating behaviour. This can influence the food choices that children make, (Thornton *et al.*, 2011). This highlights the importance of a healthy school food environment. Although the school cannot regulate the availability of unhealthy food outside the school environment, it can influence the availability within the school environment. Schools provide food for students through canteens or tuck shops. Government intervention programs have been created to help ensure that children receive a sufficient amount of nutrition. An example is the school lunch and breakfast programs enacted in states of America, (Kubik *et al.*, 2003). Schools are ideally suited to educate students about nutrition and healthy food, in order to promote healthy food behaviours. Despite these initiatives, the issue of childhood obesity continues to be of concern within the school environment. Issues stem from the availability of unhealthy and cheap food sources. A study by French *et al* (2003) states that 80% of high schools in the USA offered high fat cookies and cakes, 76% offered pizza and burgers, and 62% offered French fries; all of which are high density, low nutrition food sources. The accessibility students have to unhealthy food choices is disconcerting. Ultimately, it becomes difficult for school children to adopt healthy food behaviours when unhealthy food sources are so readily available.

The community, home and school environments are equally important in defining the childhood exposure to obesity. The role of children in the surrounding food environment is largely passive. This is particularly true in regards to the home and school food environments. Parents and teachers have a strong influence over their behaviour, attitude and access to food. The impressions that authority figures of this nature impart upon children can define whether they make healthy or unhealthy food choices in the future. However, it is also important to consider the external factors

that drive obesogenic environments. Social indicators such as social deprivation and median income are proven to strongly influence the obesogenic nature of a food environment, (Kwate *et al.*, 2009). Social and economic barriers make it difficult for people in deprived areas to access healthy foods, with unhealthy food alternatives such as takeaways and fast food being cheaper and more readily available, (Jones and Britain, 2007). In regards to children, the internal influence of authority figures from school and home food environments arguably reflects the obesogenicity of the external food environment.

3.2.2 Physical Environment

The physical environment is the second half of the obesogenic environment concept. It refers to the built and physical aspects of an environment, and has a profound influence on how individuals and communities interact within a given urban space, (Jackson, 2003). The design of the physical environment is also an important enabler in being physical active. For example, a neighbourhood with a high level of walkability is more likely to encourage people to walk, (Frank *et al.*, 2005). The inverse is also true, with areas of low walkability discouraging people to walk. Obesogenic



Figure 1 – The social influences on the physical environment

environments typically are inactive, with opportunities for physical exercise often being inaccessible, (Verstraete *et al.*, 2006). Public health intervention has been used as a solution, altering physical environments to encourage individuals to be more physically active. Figure 1 has been cited by Nassar (2015) to demonstrate how the physical environment influences the different sections of a community.

Previous research has identified three domains of the physical environment that should be targeted through intervention: recreation, transportation and occupation. The development, or neglect of these aspects of a physical environment can be a good indicator of the health outcomes in these areas.

i) Active Recreation

This refers to the available and accessibility of recreational facilities within a built up area, (JF Sallis and Glanz, 2009). Examples include greenspace, sports parks, walking and biking trails etc. Those who have access to these facilities are likely to be more physically active. This hypothesis is widely supported by previous academic literature. Blanck *et al.* (2012) suggests those with greater access to recreational facilities are far more likely to use them; this is particularly relevant among children. Children commonly use recreational facilities. The use of parks and playgrounds helps to promote a more healthy and active lifestyle, (Grow *et al.*, 2008). It allows children to have more physically exercise, as well as promote other forms of physically activity such as walking and biking for transportation, as well as recreation.

ii) Active Transportation

The availability of active transport has become a source a large debate among urban policy makers. There are many different case studies demonstrating both the promotion and reduction in active

transportation within urban landscapes. The development of processes such as urban sprawl has created cities that are far more reliant on automotive transport. The widespread creation of automobile infrastructure such as motorways has often come at the expense of active forms of transport. Thornton *et al.* (2011) states that between 1977 and 1995, the number of adults walking journeys made has decreased by 32% in the USA, something that is similarly found among children. The most common form of active transport for children is their journey to and from school. Research by McDonald (2015) has showed a decrease in the level of children who walk and cycle to school in the USA. This in turn leads to adverse health effects (the primary threat being increasing obesity rates). This trend is not reflective of all urban areas. In fact in many European countries, over 30% of all journeys are made using active transport. This is significantly higher than the falling rates within the USA, (JF Sallis and Glanz, 2009). The key difference between active transport rates in Europe and the USA is intervention. Bassett *et al.* (2008) suggests the European countries are more willingness to regulate the physical environment of urban spaces to encourage people to use active transport; examples include designing densely populated cities, discouraging car use through restricting car access and raising fuel prices. Active transport is encouraged through well organised public transport, and safe walking and biking infrastructure. Public health intervention can be used to influence population health outcomes. The mode of transport children use is highly dependent of physical tolerances of the surrounding built environment, (Larsen *et al.*,2009). Larsen goes on to suggest the needs for greater emphasis on where schools are being sited, preferably in areas of high walkability and cycle access. This would help to encourage children to use active transport to get to and from school.

iii) Active occupation and school

Active occupation refers to the how active, or inactive an individual is required to be at work. Some occupations are inherently connected to physical activity, such manual labour and sport related professions. However it is well established that the number of jobs that require physical active is declining. The global economy has become far more 'service based', with technologies limiting the availability of many jobs requiring employers to be physically active, (Tigbe *et al.*, 2011). Similar patterns of physical inactivity have been observed within schools. The physical school environment has been undervalued in previous research. Williams *et al* (2014) argues that too much emphasis has been placed on the physical environments surrounding school, rather than the physical environment of the school itself. However, in the context of obesity a schools physical environment is not considered to be a primary contributor. Much like a schools food environment, the physical environment can be influenced by education. Schools are able to provide forms of physical activity for students such as P.E classes, organised team sports and recreational facilities such as playgrounds. A study conducted by Verstraete *et al* (2006) showed that providing sports equipment to children during morning and lunch recess promoted higher levels of physical activity. This study (as well various others) has stipulated that physical activity in the school environment is well catered for. Furthermore, in the context of this study the internal aspect of the physical school environment is not the primary focus.

Active recreation, active transport and active school environments are the three most influential aspects when measuring a child's exposure to physical activity. A poorly designed built environment can be a key barrier for children who are less physically active. Less active physical environments have become more common in urban areas. Modern cities have become highly intensified and sprawled, providing less opportunity to be physical active day to day. These issues

are particularly felt in areas of high social and economic deprivation, which continues to be an ongoing issue within the obesity epidemic. However, in the context of school children, previous research has not universally identified low income areas as the least physically active environments. Research by Larsen *et al* (2009) stated that children who live in lower income areas are more likely to use active transport on journeys to and from school. Inversely children from high income areas were more likely to use motorized transport. This research identified high income families as being more financially able to drive their children to and from school, as opposed to lower income families. This study also cited distance to school as a key determinant of active transport. Those living farther away from school are more likely to use passive transport. However in the wider context of obesity exposure, school children that use active transport are still at risk of obesity. Consider the role of the food environment. Lower income neighbourhoods are more likely to have 'toxic' food environments, typically containing a disproportionately high number of unhealthy food sources, (Sisk *et al.*, 2010). Children that use active transport to and from school arguably have a higher exposure to unhealthy food sources. The key reasons for this are two-fold: Firstly, a child who uses active transport (whether it be walking, biking etc.) is more able to stop at a food outlet on the way to school as opposed to a child using motorized transport. Secondly, a child that uses active transport is often unaccompanied by an adult or caregiver, meaning the child does not have supervision to advise them on what food choices to make. Research into food preference by Ledikwe *et al* (2005) showed that children were more likely to choose high density energy foods, due mainly to their taste, convenience and relatively low cost. Given a choice, children will more likely pick the unhealthy food option. This issue is further compounded in a toxic food environment, where children are surrounded by unhealthy food sources. In short, children that are getting healthy active transport to get to and from school, are

potentially more at risk to unhealthy food outlets. This will be one of the key hypotheses in this research project. Although this may seem somewhat paradoxical, it demonstrates the importance of both the food and physical environments in determining a child's exposure to obesity. Understanding the food and physical characteristics in a neighbourhood environment is the first step to understanding the whether an obesogenic environment is present.

3.4 Mapping Obesogenic Environments

Using digital mapping techniques is the most convenient and coherent method to visually identify obesogenic environments. Mapping of obesogenic environments has been a large source of previous academic research. The identification of obesogenic environments is critical in public health intervention. Obesogenic environment are able to be identified by imbalances created between the food and physical environment. Knowing this, obesogenic environments can be visually identified and mapped, based on different aspects of the food and physical environment. Egger and Swinburn (1997) has sited the importance of mapping both the macro and micro levels of obesogenic environments, so as to better understand how the different stratified sectors of an environment influence obesity.

The use of Geographic Information Systems (GIS) has been a popular method to map previous obesogenic environments. The practical applications of GIS have been widely utilized within many different sectors of epidemiological research. GIS has revolutionized the way in which we spatially analyse public health, simultaneously identifying public health concerns and presenting solutions, (Rytönen, 2004). The real time applications of GIS make it the perfect tool to understand how a surrounding environment influences obesity. The food and physical environments are composed of a number of different aspects, making it a highly diverse concept. This is reflected in the approaches that previous research has taken to map these environments.

The following section will review some of the previous literature on measuring the exposure to obesogenic environments.

3.4 Measuring the obesogenic environment

Previous research into obesity has focused on measuring exposure to obesogenic environments. Chapter 3 of this research project has described the key components of obesogenic environment (the food and physical environments). Previous methods have used GIS to geospatially identify obesogenic environments based on the characteristics of the surrounding built environment. The food and physical components of areas are key in determining the obesogenicity of the environment. Pomerleau *et al.* (2013) stated that previous studies have focused solely on measuring either food or physical environments of an area, rather than measuring both. It is important to consider both the food and physical environments in a methodology, as both contribute to obesity exposure. The obesogenic food environment is characterised by the availability and access to unhealthy food sources. Geospatially mapping these facilities has been widely used as a method to measure exposure. Research by Raja *et al.* (2008) included all food sources (healthy and unhealthy) within a GIS analysis of the food environment in New York. This study divided the food sources into two sub categories: supermarkets and convenient stores. The purpose of this study was to identify food deserts, which were defined by a lack of food sources available in a sampled community. The majority of studies focused on the exposure to unhealthy food environments. An exception to this was research by Feagan (2007) which focused on availability of healthy food sources in a community to measure the food environment. This research examined the availability and access to small food stores supplying fruit and vegetables to the local community. This research conducted a survey, enquiring about participant's level of fruit and vegetable consumption. GIS was also used to measure the distance between participants

home and local food sources, to determine if distance from fruit and vegetable stores contributed to consumption. The results showed a positive correlation between access and consumption of fruit and vegetables. The food environment has more often measured by unhealthy food outlets, such as takeaways and fast food. Unhealthy food outlets are expected to influence the outcome of obesity, as opposed to healthy food outlets, (Fraser *et al.*, 2010). These food sources are more commonly associated with obesogenic environments, hence their inclusion in the majority of food environment measurements. Research by Jeffery *et al.* (2006) measured the connection between distance and access to fast food outlets. This GIS method used the global index network to calculate distance between home, work and fast food outlets in Minnesota. Although no significant relationship between proximity to fast food and consumption was established, the results indicated participants who ate fast food were far less likely to consume vegetables and exercise regularly. A key consideration made to this study (which is acknowledged by the author) is what constitutes healthy and unhealthy food sources. Certain food outlets are simple to classify: green grocers are clear examples of healthy food outlets; takeaways are clear examples of unhealthy food outlets. However, food outlets that sell a broad range of healthy and unhealthy products are hard to measure in an analysis of an obesogenic environment. Supermarkets the most common example of this issue, supplying a range of healthy and unhealthy food sources to customers. Research by Morland and Evenson (2009) has noted that supermarket in communities create positive health outcomes, due the availability of healthy food sources. This suggest that the positive health outcomes of supermarkets outweigh the negative. As supermarkets are hard to classify, they are often excluded when measuring the unhealthy contents of the food environment.

The connection between the built environment and physical activity can have important outcomes for public health, (Frank *et al.*, 2005). Previous research has taken a number of different

methodological approaches in how the physical environment is measured. GIS was widely used by previous literature to measure the physical environment. Mapping greenspace has been a common method used in preceding studies. Research by Sallis *et al.* (2012) has alluded to the capacity of greenspace to facilitate physically active amenities, such as parks, courts, sports field, and active transport. Despite the strong connection between greenspace and physical activity, there is minimal previous research to validate this claim. The systematic review of greenspace and health benefits by Lee and Maheswaran (2011) found weak evidence in the connections between physical health and urban greenspace, mainly due a lack of statistically significant correlations in the results. However, this review did state that accessibility and quality of greenspace were factors in levels of physical activity. This suggests that those who live in closer to quality greenspace facilities are more likely to be physically active.

Upon review, it becomes clear that distance is an important factor when measuring exposure to obesogenic environments. Not all studies found distance to be a contributing factor in their interaction with the physical and food environment. They have instead referenced social indicators such as deprivation and ethnicity as primary causes of exposure. This research project will use distance as a consideration within the research method. The key focus of this research project is obesogenic environment exposure among children. Measuring the food and physical environments of children has been a key focal point of previous research, with a particular focus on school children. The environmental exposure for school children was measured by Burgoine *et al.*, (2015) who measured the home, route, and school environment in order to determine if any correlation existed between BMI and environmental exposure. This research used GPS to map the child's route to school, and was plotted using GIS. This study found children that use active transport to and from school have lower BMI levels. However, the home environment analysis

showed that participants who walk had higher than average BMI levels. This demonstrates that transport mode can have an influence in obesity outcomes. Burgoine primarily focused on measuring mode of transport against BMI, with lesser consideration given to the food and physical environments participants were exposed to. This was considered in research by Harrison *et al.* (2014) which focused on measuring the exposure of school children to the food and physical environment. This research compared two different approaches in determining the children's route to school, GPS measured and GIS modelled. GPS measured gives a far more accurate representation of the child's route, as it is directly mapped using GPS technology. However this method does require ethics approval to complete, and takes a great amount of time to execute. GIS modelled routes used network analysis to model the route the child takes to school. This method does not require ethics approval, and is less time consuming than GPS measured routes. GIS modelled routes are not as accurate. The network analysis calculates a route from point one to another, i.e. from home to school. The network analysis route is controlled by distance, and will calculate the closest route between home and school. It is impossible to know if the modelled route is actually the route the child utilized. The results are based on pre-decided assumptions, such as the least distance and shortest time. GIS modelled routes also requires the appropriate data in order to facilitate the analysis. The route environment is a key focus of obesogenic environment exposure. Previous research by Thornton *et al.* (2011) advocates using the spatial buffer tool in GIS to measure the area of exposure to obesogenic environments. A buffer zone in GIS creates a boundary around spatial features, which allows for the measurement of obesogenic environments based on what is contained within a child's buffer zone (area of exposure). Buffer zones are an effective geospatial method to measure exposure to food and physical environments. Research by Austin *et al.* (2005) used 400 metre and 800 metre buffer zones around schools to measure the

number of fast food outlets within these predetermined areas. The results of this analysis give a numeric value, detailing the number of unhealthy food outlets within the buffer zones. This number gives a strong indication of the obesogenicity of the food environment for the sampled schools. Research by Wong *et al.* (2011) used buffer zones to measure the food environment of the GIS modelled route, identifying the area of exposure along the indicated journey to school. The application of buffer zones when measuring obesogenic environments is very effective. When measuring the food and physical environments of school children, it is important to consider all the neighbourhood environments that school children are exposed to; the primary three being home, route, and school. This research project will use buffer zones to measure the obesogenicity of the home, route and school environments that school children are exposed to. The obesogenic environment will be measured by the food and physical environments within the school children's exposure area (buffer zone). It is hoped that this research will be able to determine a connection between the environmental exposure to obesity and the obesity outcomes of school children in New Zealand.

Summary

Thus far, this research project has outlined the global context of obesity and obesogenic environments. The previous literature relating to mapping and measuring obesogenic environments has helped to shape the research method used for this project. Chapter 4 of this study will narrow the scope of focus to New Zealand. Obesity is an important public health issue within New Zealand, and will be explained and discussed in the following chapter of this research project.

Chapter 4 – Childhood Obesity in New Zealand

Chapter Summary

This chapter will outline how obesity has become one of the most severe public health concerns within New Zealand. The context of obesity within New Zealand will be clearly established, with particular reference to how different demographics within New Zealand are differentially influenced. The second section of this chapter will focus specifically on rising levels of childhood obesity, and discuss how obesity is currently being approached by New Zealand policy makers. The city of Hamilton will also be introduced to the reader, as it is the focus of the geospatial analysis section of this research method.

4.1 Introduction

Obesity is one of the most severe public health issues in New Zealand. The prevalence of obesity over the last years 30 years has led health authorities to label obesity as a health epidemic. New Zealand's obesity rate is extremely high. Statistics New Zealand has stated 28.4% of New Zealanders are obese. An OECD report released in 2014 has ranked New Zealand third in the OECD for obesity rates, (OECD, 2014). Only Mexico and USA rank higher. The following information is demonstrated on the Statistics New Zealand Table below.

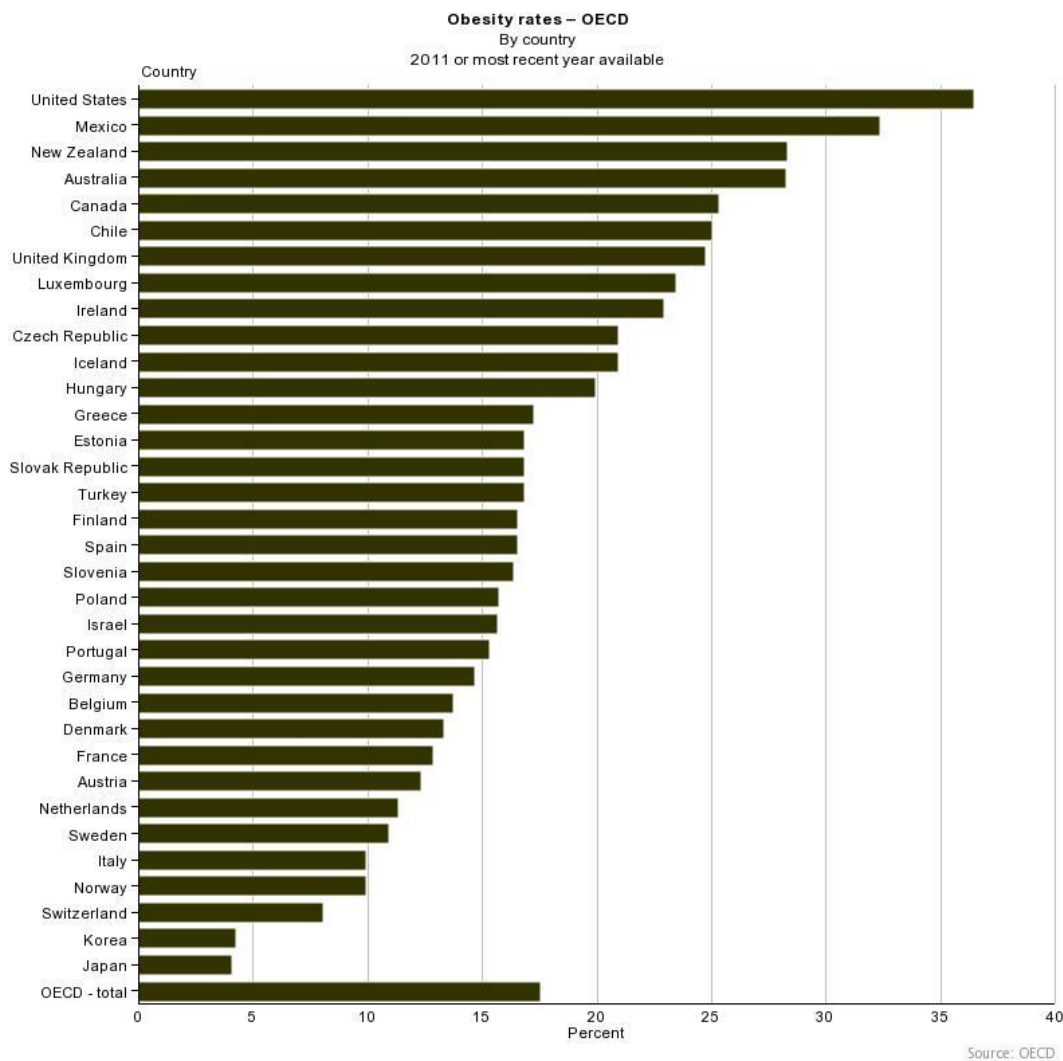


Figure 2 Obesity rates – OECD

Figure 2 shows a high number of developed countries featured on this list. The increasing prevalence of obesity among developed countries has been a large concern. Many of these OECD countries have seen large increases in obesity prevalence. The rate of obesity increase in New Zealand has been no exception. The NZHS found that the rate of obesity among New Zealand males has increased from 17% in 1997 to 30% in 2012/2013. This increase was mirrored among females, from 21% in 1997 to 32% in 2012/2013, (Ministry of Health, 2012). This report states that over the last 15 years, there has been 44% increase in obesity prevalence over the entire country, (pg22).

The high rate of childhood obesity is one of the major concerns in the New Zealand obesity epidemic. Approximately one in three New Zealand children aged 2-14 years old are overweight.; 11% of these children are obese, (Ministry of Health, 2015). The high rates of childhood obesity present a number of negative health impacts for individuals. Serdula *et al.* (1993) has shown that children who are overweight or obese have a greatly increase chance of being overweight or obese as adults. There are also a number of physical and psychological health related illnesses that can result from childhood obesity, such as disrupted sleeping patterns and poor self esteem.

The NZHS Key Findings report 2012/13 found discrepancies between parental perception of their child's weight and their actual BMI status. A large number of children that were sampled within the NZHS 2012/13 believed their child to have a healthy weight status, when in reality their BMI status indicated a large number of these children were overweight or obese. This trend was most common amongst children aged 2-4. 9 out of 10 parents believed that their child was neither underweight nor overweight. According to the results of NZHS 2012/2013, 32% of children aged 2-4 years old were overweight. This shows a large disparity between how parents perception of

their child's weight and the child's actual weight. This statistic is represented in Figure 3, which shows parental weight perception for children aged 2-4, 5-9 and 10-14 respectively.

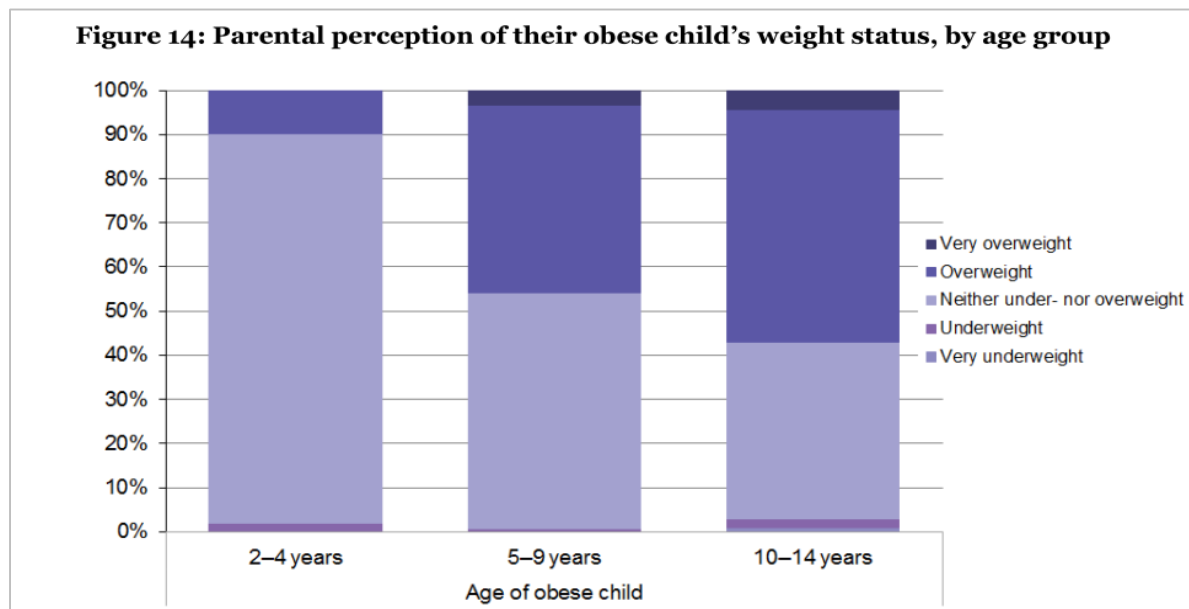


Figure 3 Parental perception of their obese child's weight status, by age group

This research project has already stated that obesity has not always been viewed as an unhealthy characteristic among children. A child's overweight status has historically indicated well-nourishment and wealth. This could potentially explain the large number of parents who misevaluated their weight status of their child. It is also important to consider the child's age. This issue was most prevalent among children aged 2-4. Research by Mei *et al.* (2002) has alluded to the difficulties of evaluating a young child's weight status, as their bodies have not fully developed to display the characteristics that indicate overweight or obesity. The Ministry of Health (2015) has suggested that a general increase in childhood obesity has altered what parents consider to be healthy or normal body image. The encouraging trend from Figure 3 is the decreasing amount of parental misconception on weight among children aged 5-9 and 10-14.

The next section of this chapter will focus on the specific demographic grouping that are adversely effected by the obesity. The three key demographic focus areas will be age, ethnicity and social deprivation.

4.1.1 Age

Age is a determinant in obesity. It is important to understand how different age demographics are influenced by obesity. The obese proportion of the New Zealand population aged 15 years and over is displayed on the Figure 4.

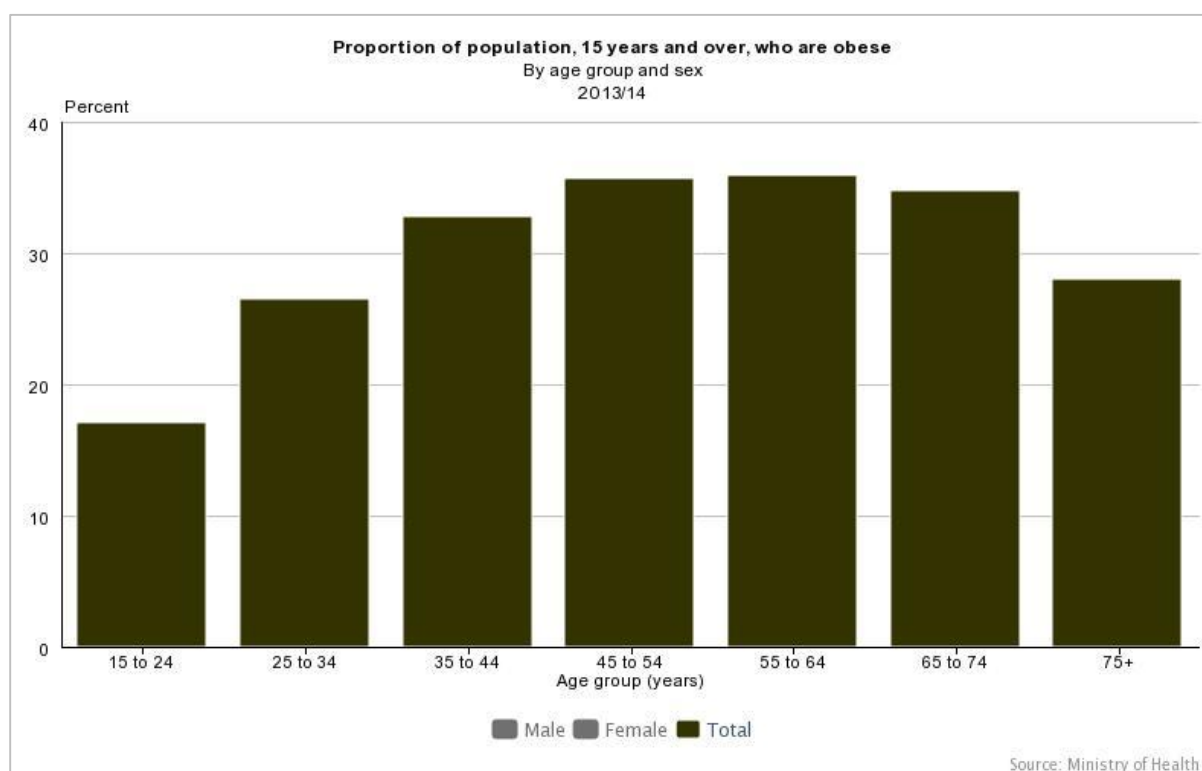


Figure 4 Proportion of population, 15 years and over, who are obese

Figure 4 shows that New Zealanders aged 45 to 54 and 55 to 64 have the highest rates of obesity in the New Zealand population at 36%. The 35 to 44 and 65 to 74 age groups are only slightly

less, with 32.8% and 34.8% respectively indicated as obese. This shows that middle aged individuals in New Zealand are the most likely to obese. This graph also shows that the obesity rate among those aged 15-24 is 17.9%. This is not as high as the population aged 35 to 64, however it is still of concern. As is mentioned above, obesity in childhood is often continued into adulthood, which means a large proportion of these children are at risk of continuing to suffer from obesity, as well as the negative health consequences in later life. The proportion of the New Zealand population aged 2-14 is represented on Figure 5.

Table 15: Sociodemographic characteristics of children, by BMI category, 2011–2013						
Characteristic	Thinness (%)	Healthy weight (%)	Over- weight (%)	Obese (%)	Obese I (BMI 30.0–34.9) (%)	Obese II (BMI ≥ 35.0) (%)
Boys	3	65	20	11	6	5
Girls	4	63	23	10	6	4
Ethnic group						
Māori	3	53	26	18	10	8
Pacific	1	45	28	26	14	12
Asian	7	68	19	7	4	2
European/Other	4	70	20	7	4	3
Age						
2–4	4	64	22	10	4	6
5–9	3	67	19	11	6	5
10–14	4	62	24	11	8	3
Deprivation						
Q1 (least deprived areas)	4	76	17	3	3	0
Q2	4	69	18	8	5	3
Q3	4	68	20	8	5	4
Q4	3	63	21	12	7	5
Q5 (most deprived areas)	3	51	27	19	10	9

Figure 5 Sociodemographic characteristics of children, by BMI category. (Ministry of Health, 2015)

This graph shows very little variation in the weight status of children aged 2-14. Across the three age categories given (2-4, 5-9 and 10-14) the percentage of children is relatively similar for each

weight status. A large proportion of children aged 2-14 have a healthy weight, 64% being the mean average across the three age categories. As is stated above, one third of New Zealand children are either overweight or obese. Children aged 2-4 and 5-9 have similar rates of overweight or obesity within the population at 32% and 30% respectively. Children aged 10-14 were slightly higher at 35%. Despite these differences, there is very little variance between the percentage of overweight and obese children aged 2-14 in New Zealand.

4.1.2 Ethnicity

Ethnicity is a significant indicator of obesity in New Zealand. Previous editions of the NZHS have highlighted the large disparities in obesity rates in the context of ethnicity in New Zealand. The following graph shows the percentage of obesity within the different ethnic groupings in New Zealand.

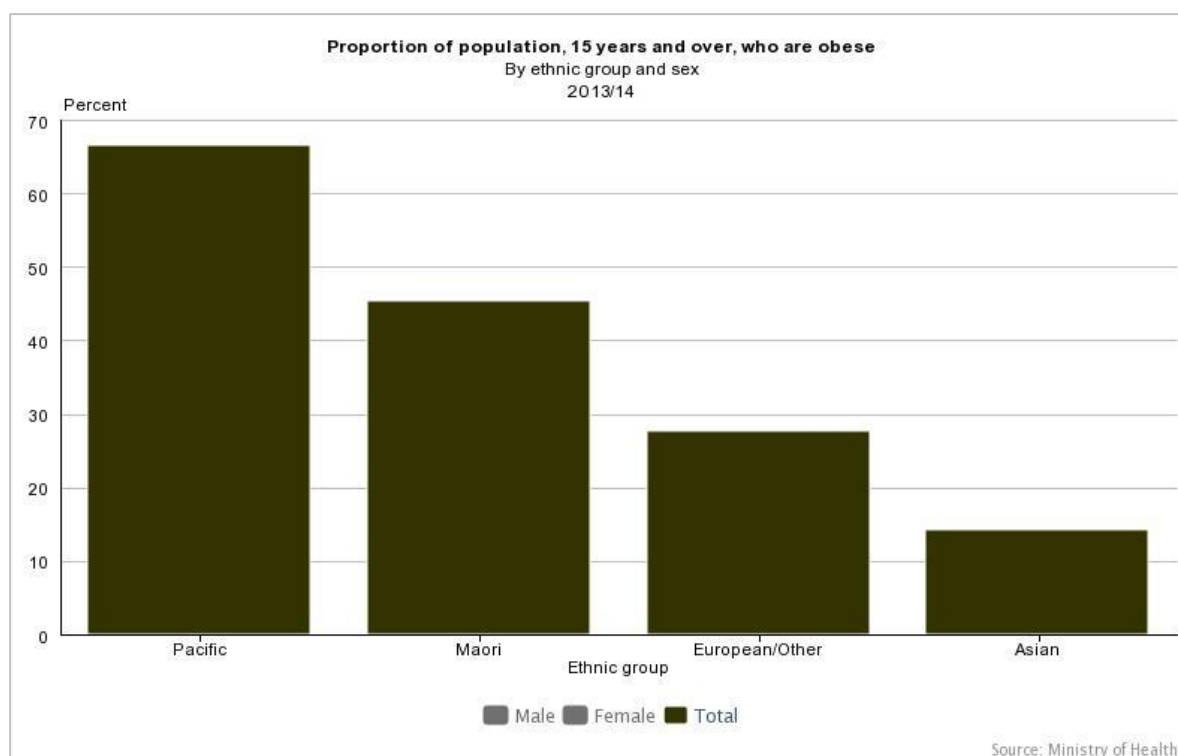


Figure 6 Proportion of population, 15 years and over, who are obese by ethnic groups and sex

The most significant finding from Figure 6 is proportion of Pacific Islanders who are currently obese in New Zealand. 66.8% of Pacific Islanders suffer from obesity, which is significantly higher than the Maori, European and Asian ethnicities. The Maori population also has a very weight rate of obesity. 45.5% of Maori obese; this is not severe as Pacific Islanders, however is still well above the national average of 28.4%. Both the Maori and Pacific Island population are disproportionally effected by obesity in New Zealand. This trend is reflected in Pacific Islander and Maori children. Figure 5 shows 54% of all Pacific Island children aged 2-14 were classified either overweight or obese, which represents over half of the total child population sample; 26% of these children were considered obese. Maori children demonstrated lower levels of obesity among children aged 2-14, with 44% considered overweight or obese. However, as is the case amongst adults, the childhood obesity rate amongst Maori was still well above the national average. Asian children aged 2-14 were shown to have the lowest rates of obesity with 26% being overweight or obese. This was just below the European/Other obesity rate of 27%. This information clearly demonstrates some significant connections between obesity rates among Pacific Island and Maori. This connection will be an important consideration for this particular research study.

4.1.3 Social Deprivation

Social Deprivation is shown to have a significant influence on an individual's likelihood of obesity. In the context of this study, social deprivation refers to area deprivation. The NZHS 2013/14 expresses area deprivation using (CAU) Census area units and (MB) Meshblock information of a household as derived from the Census, (Ministry of Health, 2014a). The connection between social deprivation and obesity has a key finding in many previous additions on the NZHS. Adults that live in deprived areas have an increased likelihood of being overweight or obese. The NZHS

(2013) Key Findings report found that 44% of adults that lived in the most deprived areas were obese, in comparison to 21% in the least deprived areas. This report states that adults in deprived areas are 20% less likely to be physically active, as well as less likely to eat at least two serving of fruit per day. These two findings suggest that adults in deprived areas are less likely to eat healthy food and exercise, which is a significant foreshadow to obesity.

Similar trends are observed amongst New Zealand children who live in deprived areas. The NZHS (2014) found that 19% of children living in the most deprived areas were obese. This is significantly higher than the 3% of children living in the least deprived areas, (see Figure 5). There are a number of negative health outcomes that children in deprived areas are more likely to experience. 26% of children in deprived areas have an unmet need for primary forms of healthcare. This is significantly higher than children in the least deprived areas (13%), (Pg51). As was alluded to above, there are a high number of parents who have perceived their child's weight to be normal, when in reality their BMI suggested they were either overweight or obese. The Ministry of Health (2015) revealed that the majority of these cases occurred in deprived areas. This report attributed the lack of education around healthy body image as a contributing factor to this occurrence. The connection between ethnicity and social deprivation is an important consideration in context of obesity in New Zealand. Pacific Island and Maori are the most adversely effected ethnic groups in New Zealand. It is also significant that a high number of the Pacific Island and Maori population live in deprived areas. Salmond *et al.* (2006) has noted that Pacific Island and Maori have a disproportionately high number of their population living in deprived areas. The connection between social deprivation and obesity has been strongly established in previous research, which puts ethnicities such as Pacific Island and Maori at a disadvantage. This concept is known as environmental injustice. Environment justice is defined by Taylor *et al.* (2006) as "efforts to

address the disproportionate exposure to and burden of harmful environmental conditions experienced by low-income and racial/ethnic minority populations”, (Pg1). This term is directly applicable to Pacific and Maori ethnicities in New Zealand, who are disproportionately exposed to obesity based on the characteristics of their environment. Environmental justice in the context of obesity was a key catalyst in the obesogenic environment concept, which in the environment is an important determinant in obesity exposure. Social deprivation will an important consideration in the application of this research project. The connection between obesity and social deprivation is predicted to be one of the key findings in this research.

4.2 Obesity Response in New Zealand

The obesity epidemic is currently a source of much debate and discuss in New Zealand context of health. The next section of this chapter sets out to explain how New Zealand as an entity is responding to obesity. This section will be focusing on the previous academic research around obesity in New Zealand. This will be done with close reference to specific case studies on obesity and obesogenic environments. This section will also discuss the health related action New Zealand is taking to reduce the prevalence of obesity.

The high rates of obesity in New Zealand have triggered a national debate among various persons and entities within the New Zealand health system. New Zealand Health Minister Jonathan Coleman has recently spoken out against the high rates of obesity. Coleman has stated the need to introduce a health target to reduce the rates of childhood obesity. (Johnson, 2015). This suggests the New Zealand government is now recognizing the need to respond to obesity. However based on previous literature reviews of obesity health interventions, appropriate and effective action can be difficult to determine. A study by Saguil and Stephens (2012) conducted a

literature review of all the previous obesity health intervention programmes. This study alluded to three intervention programmes that have been introduced in New Zealand. All of these studies focused on reducing obesity rates among children. Two of these studies focused on school based programmes to reduce the rates of obesity. A Pilot Programme of Lifestyle and exercise (APPLE) programme was designed by the University of Otago, and focused on children aged 5-12 across 7 different primary schools within the Otago region. The intervention initiatives of the APPLE programme focused on two key areas: educating children about healthy nutritional choices and increasing the amount of physical activity by creating noncurricular exercise programmes such as community walks, (Rachael W. Taylor *et al.*, 2007). The results of this study show this relatively simply intervention strategy increased participation in physical activities and acted to slow significant weight gain among children from the selected schools, (Rachael W. Taylor *et al.*, 2006). This study is an example of a community based health intervention programme. This intervention strategy shows how low cost, high participation health interventions can be effective within a community. A similar approach was taken for the 'Project Energize' obesity intervention programme. This policy focused on a much larger geographic scale, with all 235 school in the Waikato region being eventually incorporated into this intervention strategy. There were five defining attributes that distinguish Project Energize from previous obesity interventions, (Waikato District Council *et al.*, 2011).

- 1.) The way in which it encourages children to adopt a healthy lifestyle choice but not in exclusion of their family's and the wider community. Specifically, it aims to increase children's activity levels 1 reduce sedentary time, and optimise nutritional intake.
- 2.) It is a 'long term' [i.e. 2005-2011) project.

- 3.) Although a series of pre-post measures are for determining impact on some variables, this project recognises that the instructional processes need to be contextually and culturally suited to the respective school environment.
- 4.) This is a project involving a range of partners from public and private sectors. Although Project Energize is very closely aligned with the Health and Physical Education curriculum there has been little involvement from the Ministry of Education.
- 5.) Schools in the Waikato DHB region have acknowledged a potential 'crisis' in the health and wellbeing of our children and voluntarily embraced the ethos of Project Energize as a research project designed with the school for the benefit of their children. (pgII)

The Waikato DHB assigned each participating school a health co-ordinator. Their primary focus was to facilitate the broad games of healthy eating habits and increasing physical education and participation, (Saguil and Stephens, 2012). The results of this programme demonstrated a number of positive health outcomes for the participants in Project Energize. One of the key findings was an increased willingness to participate in physical activity. This was also small decrease in children's BMI status in comparison to the studies control group, (Rush *et al.*, 2014). Both the APPLE and Project Energize strategies were examples of affordability and effective obesity prevention programmes. Education was a primary focus of both these programmes, making the school environment an ideal medium for obesity intervention programmes to be introduced.

These intervention programmes have proven to be effective within the context of their focus area. However very few effective programmes have been focused on a New Zealand wide scale. As a result, intervention programmes have been unable to slow the national rate of obesity within New

Zealand. If New Zealand is to achieve a health target as the government has suggested, intervention needs to be implemented on a national scale. The implementation of a sugar tax has been an intervention policy proposed by public health organisations to reduce obesity. The purpose of a sugar tax is to reduce the amount of sugar consumption within a population by taxing the sale of food and drinks with high sugar content, (Wang *et al.*, 2012). This is intended to act as an economic incentive to discourage consumers from buying food containing high amounts of sugar, most of which is typically highly affordable. Sugar has been a large source of debate within New Zealand. Previous entities within New Zealand have referenced the high level of sugar content within the average diet on New Zealanders. A New Zealand Medical Journal Article by Walls *et al.* (2014) has alluded to the high level of sugar consumption in New Zealand (particularly among children) as one of the key drivers in high obesity rates, as well as a factor in increasing rates of Type 2 diabetes and cardiovascular disease. This study cited the high consumption of non-alcoholic or sugary drinks as one of the key sources of sugar intake, which is the basis for recommending the implementation of a sugar tax in New Zealand. The positive health outcomes of implementing a sugar tax have been evident in previous case studies. Mexico is often referenced as an example of a successful sugar tax initiative. Mexico has one of the highest obesity rates in the world. They are currently second, one behind the United States, (see Figure 3). In 2010, Mexico introduced sweeping regulation across their public health sector in an attempt to reduce obesity rates. A sugar tax was one of the key aspect of this strategy. This particularly focused on prevention among children, with initiatives created to ban soda and regulate unhealthy food options within Mexican schools, (Barquera *et al.*, 2013). Despite the short term existence of the sugar tax, Mexico has already seen positive behavioural change in regards to healthy food choices. In the first half of 2014, sales of Coca Cola were reported to have dropped by 6.4%, (Guthrie,

2014). This demonstrates that there has been a decrease in the consumption of non-alcoholic sugary drinks, which has been referenced by many previous studies as one of the key sources of high sugar intake. The implementation of the sugar tax has not been in place long enough to generate a drop in obesity rates. However it does appear to be reducing sugar consumption, which will have positive health outcomes in the future. Further research has suggested that sugar tax can help to lessen the economic burden that obesity can place on a countries public health system. Chapter 3 of this study outlined the high economic cost of obesity. However even a modest tax on sugar can generate large economic profit. Popkin *et al.* (2009) stated that a nationwide tax increase of 1% per ounce of sugar in the USA would generate \$14.9 billion in annual revenue. This will not only offset the economic cost of obesity, but also provide fiscal resources for further obesity intervention programmes. Giving the success that sugar taxes have had in other countries, the implementation of a sugar tax in New Zealand has been a popular recommendation. The National Institute of Health Innovation (2014) has advocated for the introduction of a sugar tax in New Zealand, stating the a 20% tax on sugary drinks could save 67 lives per year. The current New Zealand Health Minister Jonathan Coleman has ruled out the implementation of a sugar in New Zealand, alluding to a lack of evidence indicating a sugar tax would be effective within the context of New Zealand health, (Watkins, 2015). Despite the popularity of the sugar tax in New Zealand, there have been no notable studies to date testing the viability of a sugar tax in New Zealand. The sugar tax debate has only recently started to gain relevance within New Zealand politics and media. More evidence based research is needed in order for meaningful health intervention to be considered in the future. This study will not attempt to test the viability of a sugar tax, or indeed any other forms of health intervention or regulation in the context of obesity in New Zealand. The primary focus of this studies is to analyse the connection between obesogenic

environments exposure and BMI levels among school children. This study is the first of its kind within New Zealand. The analysis of the home, route and school environment is unique within the context of obesogenic environment research in New Zealand. It is hoped that this study can serve as a foundation for future research into the connections between obesity and the environment in New Zealand.

4.3 Hamilton City

Hamilton is a city located in the North Island of New Zealand. It is New Zealand's fifth largest city, with a recorded population of 141,612 as of June 2014, (Statistics New Zealand, 2014). The geospatial analysis of this research is based in Hamilton. This was requested by the New Zealand Ministry of Health, who is directly funding this research project. Hamilton is located in the Waikato region in the North Island of New Zealand. The Waikato District Council was actively involved in supplying data to help conduct this research project, providing a list of all the food outlets within Hamilton city. There is currently no significant research indicating obesity levels on Hamilton. There have been previous obesity interventions conducted within the Waikato region, which have been directly targeted at children. Project Energize (an obesity intervention programme for school children) was conducted in the Waikato region, with a number of Hamilton school involved. It is hoped that this research project can provide insights into the childhood obesity rates in Hamilton. This will beneficial information for intervention programmes in the future.

4.4 Summary

Chapter 4 of this research project introduced the reader to obesity in New Zealand. This chapter helped to establish the severe threat that obesity poses to the New Zealand public health in the future. The response to obesity in New Zealand has also been explained. While it is stipulated that obesity prevention is needed in New Zealand, there is little indication to suggest that meaningful policy will be implemented in the near future. The information presented in Chapters 2, 3 and 4 represents the body of work reviewed to create the research method of this project. Previous research into obesogenic environment, (particularly in regards to GIS mapping and measuring) were essential in creating an appropriate research method for this project. The demographic information reviewed in Chapter 4 was considered when gathering information from the NZHS 2013/2014. The important social indicators in the context of New Zealand obesity (such as social deprivation and ethnicity) will be carefully considered in part 1 and part 2 of the research method. Chapter 5 will describe the method in this research project.

Chapter 5 – Method

Summary

This chapter will comprehensively outline the methodology that was used to complete this research project. This project used a quantitative method, utilizing geospatial and statistical tools to determine the connection between children's exposure to obesogenic environments and BMI status. This method uses statistical data from the 2013/2014 NZHS for children aged 5 to 14. The research method was conducted in two parts:

1) New Zealand wide analysis

Part 1 of this research method is a nationwide analysis of NZHS children. Part 1 will explore the connection between BMI and the responses given by children in the NZHS. Age, social deprivation, mode of transport, and ethnicity will be the key areas of focus. There were 2404 participants selected for this analysis.

2) Hamilton City analysis

Part 2 of this research method focuses on the New Zealand city of Hamilton. This method will geospatially examine the correlation between the food and physical environments, and BMI outcomes of NZHS children in Hamilton. This method uses GIS to create the food and physical environment in Hamilton. This method will also use network analysis to model the most likely route NZHS children take to school, in order to examine the participant's exposure to obesogenic environments. Exposure will be measured by buffer zones created around the home, route and school environment of the NZHS participant. There were 70 participants selected for this analysis.

5.1 Introduction

The key aim of this research project is to examine the relationship between exposure to obesogenic environments and health outcomes among children. The participants considered within this study were all the children aged 5 -14 in the NZHS 2013/2014. The method of this research project was conducted in two parts. Part 1 focused on a nationwide statistical analysis of children aged 5-14 within the NZHS. Part 2 conducted a geospatial analysis of all children aged 5-14 within the city of Hamilton. Both of these methods examined the correlation between a participants BMI status and selected responses participants gave in the NZHS.

5.2 Data Sources

The following section outlines the key data sources that were used to complete the method in this research project.

5.2.1 NZ Health Survey

The New Zealand Health Survey (NZHS) is a research survey commissioned by the Ministry of Health. The most recent survey was commissioned in 2013/2014. The following goal is stated in the 2013/2014 NZHS report:

“The goal of the NZHS is to support the formulation and evaluation of policy by providing timely, reliable and relevant health information. This information cannot be collected more efficiently from other sources, and covers population health, health risk and protective factors, and health service utilisation”,
(Ministry of Health, 2014, Pg 1)

This research focused only children aged between 5 and 14. These age groups represent children that used active transport to school in the NZHS. Active transport is defined by the Ministry of Health (2014b) for children (aged 5 to 14) travelling to and from school by walking, cycling, or other non-motorized modes. One of the key predications of this study was that mode of transport does influence obesity, therefore children aged 5 to 14 will be the key age demographic used in this research.

5.2.2 Control Variables

The following is a list of the NZHS considered within this research project

Table 1 List of NZHS variables

Sex	CD.02	And are they male or female?
Age group	CD.03a & b & c	2-4, 5-9, 10-14
Nutrition	C3.07	On average, how many servings of vegetables does [Name] eat per day? Please include fresh, frozen or canned vegetables. Do not include vegetable juices.
Nutrition	C3.08	Thinking back over the past 7 days, on how many days did [Name] have breakfast at home?
Nutrition	C3.09	In the past 7 days, how many times did [Name] have a fizzy or soft drink, such as cola or lemonade?
Nutrition	C3.10	In the past 7 days, how many times did [Name] eat food purchased from a fast food place or takeaway shop, such as fish and chips, burgers, fried chicken or pizza? This includes snacks as well as mealtimes.

Physical activity	C3.11	How does [Name] usually get to and from school?
Height	CM1.0	If aged 2+ years
Weight	CM2.0	If aged 2+ years
Waist	CM3.0	If aged 5+ years

Table 1 shows the wide range of variables considered for this project. The two most important variables are physical activity [mode of transport to school] (C3.11) and BMI (CM1.0 and CM2.0). BMI is the dependent variable for this research. Physical activity, as well as the other variables shown in Table 1 are the independent variables for this research. Variable such as age, sex, and ethnicity will seek to identify social indicators of obesity among participants. This will determine to what extent these demographics influence BMI.

The remaining independent variables shown in Table 1 will be used for the individual and environmental characteristics that influence obesity exposure. The nutrition questions measured the nutritional value the child is getting from their food environment, both within the context of the home and commercial food environment. Initial predictions suggest that a child would poor nutritional value within their weekly diet would be more exposed to obesity, and by association have a higher BMI level. The food security questions seek to analysis the home food environment of participants. These questions are closely aligned with social and environment indicators, such as social deprivation and median income. Families with the inability to afford healthy food on a regular basis would be expected to have a greater exposure to obesity, due to lack of nutritional

value and consistency in their weekly diet. All of the variables on Table 1 were predicted to have an influence on participants BMI status.

5.2.3 Participant Privacy and Safety

The privacy and safety of NZHS participants was an important consideration within this research method. It was important that the participants used in this research remained anonymous throughout this process. This is primarily to ensure the safety of those who were chosen for the purpose of this study (that is children aged 5 to 14). Participant privacy was not a major consideration for the nationwide analysis section of the method. This section was purely statistically based analysis, using regression techniques. It was completed using the statistic programmes of Microsoft Excel, R and SPSS statistics. The nationwide analysis did not require the geographic location of the participants to be known, as Part 1 did not focus on environment exposure. Therefore participant identification was not possible, as no geographically related variables were used in any form of the nationwide analysis. Participant privacy the most important consideration to make in the Hamilton city geospatial analysis. Environment exposure to BMI was the primary focus of this section, hence geographic variables were an important component. The key aim of this section was to identify obesogenic environments in Hamilton. This requires geospatial data for the food and physical environment in Hamilton (primarily unhealthy food outlets and greenspace). GIS was used to create the food and physical environments in Hamilton in order to gauge the spatial distribution of these facilities. 70 participants were selected for the Hamilton City analysis case study. Participants that were eligible for this study were required to be:

- Participants in the NZHS 2013/14
- Living within Hamilton – as defined by the Hamilton City boundary area, (StatsNZ, 2015)

- Aged 5-14 – school children were required to participate in this study, as one of the primary focuses was to measure the environment of the participant's most likely route to school.

The meshblock identification number of the participants sampled in the NZHS was recorded by the Ministry of Health. However this information is not available to the public for the safety of the participants. In order to identify participant eligible for this research project, the Ministry of Health independently identified children aged 5-14 who lived in Hamilton. The information was provided with the meshblock ID number removed; this process will be further explained later in the chapter. This ensured that there was no geographic reference or information in which the participants in this study could be identified. The address, neighbourhood or suburb of any participants in this study is unknown to this researcher. The fact the participants live in Hamilton is only geographic knowledge that is known about the 70 children in this research. The use of NZHS data required this study to carefully consider how the research method will ensure that participant information was not used in any way to compromise their privacy and safety. The information provided by the MOH was only seen and accessed for the purpose of this research project.

5.2.4 Otago Social Deprivation Index

Social Deprivation of participants was an important consideration within this research project. Chapter 4 of this research outlined the important connection between BMI and Social Deprivation. It was therefore necessary to include the social deprivation of participants, given the well-established connection between deprivation and obesity. This study used the Social Deprivation Index created by the University of Otago. This research project uses the most recently updated index, which is the NZDep2013. The NZDep2013 index is derived by using 9 variables from the 2013 New Zealand Census. These variables are listed on Figure 7:

Dimension of deprivation	Description of variable (in order of decreasing weight in the index)
Communication	People aged <65 with no access to the Internet at home
Income	People aged 18-64 receiving a means tested benefit
Income	People living in equivalised* households with income below an income threshold
Employment	People aged 18-64 unemployed
Qualifications	People aged 18-64 without any qualifications
Owned home	People not living in own home
Support	People aged <65 living in a single parent family
Living space	People living in equivalised* households below a bedroom occupancy threshold
Transport	People with no access to a car

Figure 7 Dimension of deprivation defining by NZ Census 2013

(Salmond *et al.*, 2006)

The NZDep2013 index can be used at both CAU and MB level. This research project considered social deprivation at MB level. The NZHS participants selected for this study were represented at meshblock level, which is the smallest boundary unit in the New Zealand Census. This index does present a limitation. The NZDep2013 index gives a representation of the surrounding environment of the NZHS participants, not the actual Social Deprivation of the participants themselves. This can potentially lead to ecological fallacy corrupting the results. However in the context of this study, the NZDep2013 will still represent the deprivation of the surrounding environment, which this research has established as an important determinant in an obesogenic environment. Chapter 4 of this research has already alluded to the connection between obesogenic environment and highly deprived areas. The NZDep2013 is therefore measuring the child's area exposure to deprivation.

5.3 Part 1: Nationwide Analysis

Part 1 of the research method focused on the NZHS children aged 5-14 nationwide. There were 2404 nationwide children identified in the NZHS that were sampled in the nationwide analysis. The NZHS data for this research project was provided by the New Zealand MOH. This research project has already alluded to the importance of participant safety in the design of this method. This researcher was not able to know any geographic information that would make it possible to identify the participants used for Part 1 of the research analysis. The MOH provided a list of all children aged 5-14 sampled in the NZHS, attaching all the required variables listed in Table 1. This information did not contain any geographic information about the participants, ensuring the safety and privacy of the participants. The dataset sent from the MOH identified a total of 4379 children aged 5-14 in the NZHS. Some of these children had to be removed for the nationwide analysis, as not enough participant information was provided to make these participants applicable to this research project. The children were identified within this study based on two characteristics

- 1) Aged 5-14
- 2) BMI status

The aim of this research focused on the BMI outcomes for school children. Participants were required to attend school in order to be applicable for this research project. The NZHS samples children aged 2-14. Children aged 2-4 are not yet old enough to attend school in New Zealand, and therefore were eliminated from this study. The maximum age for participants sampled for the NZHS variables in Table 1 was 14 years old. The second requirement of this research project was the participants' BMI status. The NZHS sampled BMI by measuring the height and weight of participants. BMI is the most important variable used in this research project. Participants were required to have a BMI level available in order to identify their weight status. There were a number

of children aged 5-14 that were eliminated from this study as their BMI status was not given, meaning the child was either unwilling or unavailable for height and weight measurements. These participants were therefore excluded from this research project. Given these considerations made for age and BMI status, there were 2404 children identified nationwide for this research project.

5.3.1 BMI vs Mode of Transport

The key aim of the nationwide analysis was to determine the connection between BMI and the mode of transport used by participants to and from school. The NZHS listed seven alternative mode of transport for children:

- 1) Walk
- 2) Bike
- 3) Skate or other physical activity
- 4) Car
- 5) School bus
- 6) Public transport
- 7) Other
- 0) Not applicable, for example, is home schooled

The NZHS participants were asked which mode of transport they normally use to get to and from school. Multiple responses to these questions were possible. For the purpose of this research method, the categories of 'Other' and 'Not applicable' were not considered within any analysis. Their mode of transport was unknown, and therefore is irrelevant to the nationwide analysis. Walk, bike and skate are considered active forms of transport. The participants that use these modes can be considered more physically active, as they are using physical activity within their journey to and from school. For the purpose of this study, 'Public transport' was included under the 'Bus' category. This was due both to the low number of participants that used public transport, and the similarity of public transport and bus as a transport mode. Car and bus are considered passive

forms of transport. Participants that used these modes of transport are less physically active based on information from the NZHS, as they are gaining less physical activity on their route to school compared to active transport users.

This research method used a linear regression analysis to determine if a correlation exists between a participant's BMI and their mode of transport. This regression model was created using SPSS statistics. The dependent variable used within this analysis was participant BMI; the independent variable was the participants mode of transport. A separate regression model was run within SPSS statistics for each different modes of transport (walk, bike, skate, car, bus). The purpose of this regression analysis was to determine if the mode of transport to and from school has any effect on the BMI outcomes of participants.

5.4 Part 2: Hamilton Geospatial Analysis

Part 2 of the research method is specifically focused on Hamilton. The MOT (who directly funded this research project) requested that Hamilton should be the chosen case study. This method focused on Hamilton children aged 5-14 identified in the NZHS. The key purpose of this method was to identify the relationship between participant BMI and the surrounding food and physical environments. This method incorporates the geospatial characteristics of the participant's food environments (unhealthy food outlets) and physical environments (greenspace). Exposure to obesogenic environments was measured by the number of unhealthy food outlets and greenspace contained within the home, route and school environments of participants.

5.4.1 Creating the Obesogenic Environment

The geospatial characteristics of the food and physical environment in Hamilton had to be created before the NZHS children could be identified. The food and physical environments in Hamilton were created using the GIS software programme ArcMap. The following section describes the GIS method used to create the food and physical environment in Hamilton. The first step in the GIS method was to identify the focus area in Hamilton. A boundary map of Hamilton city is

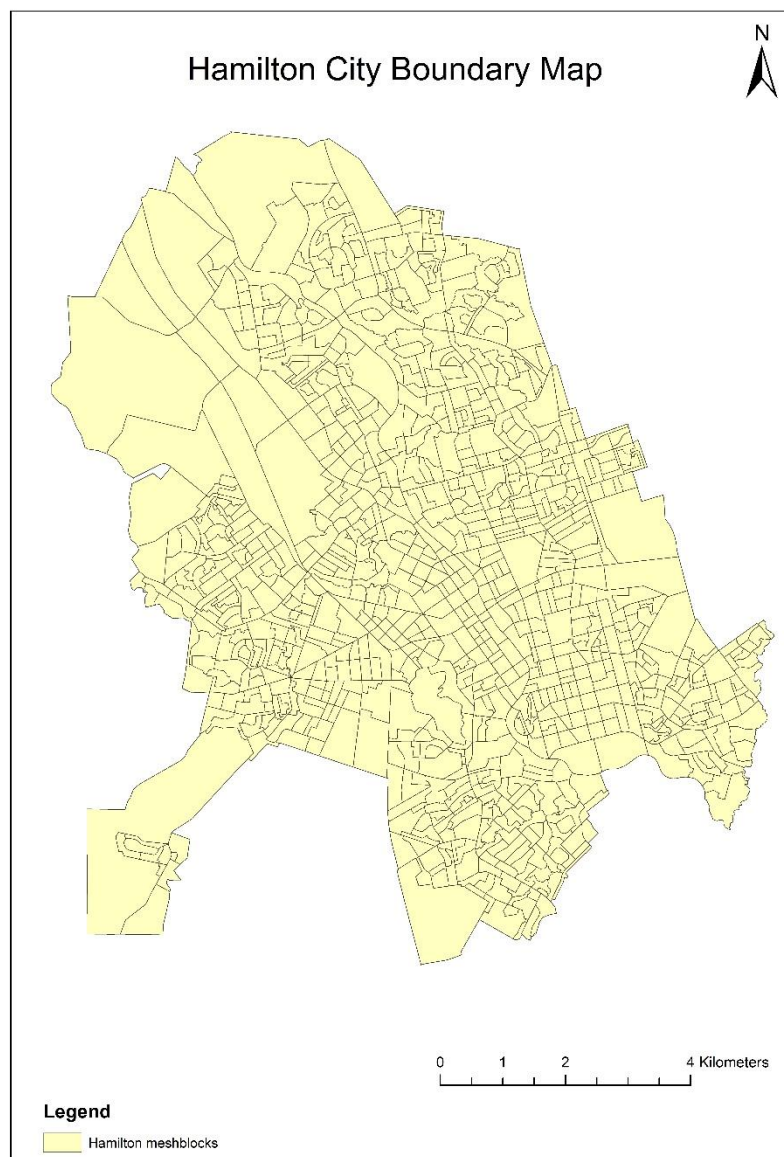


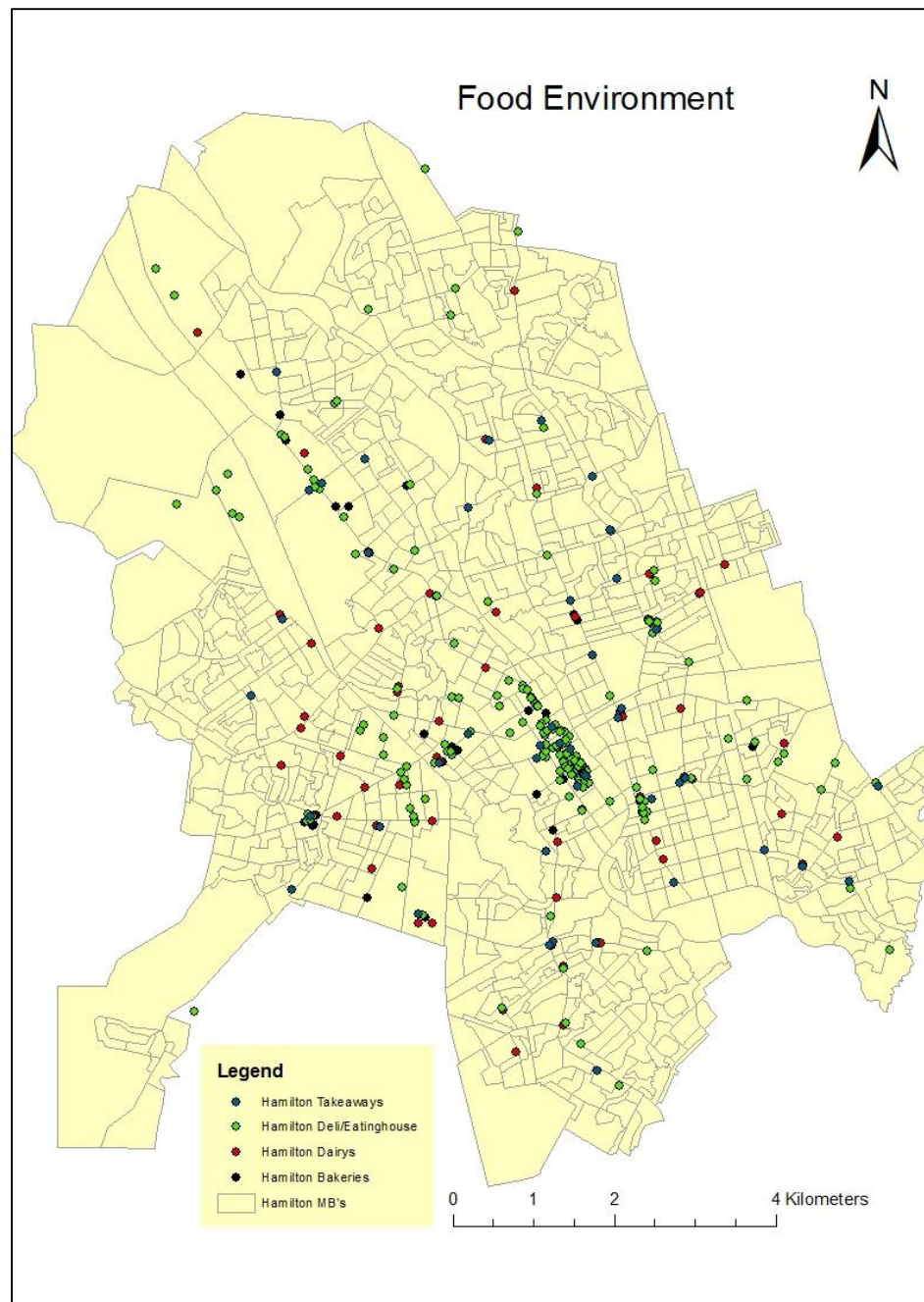
Figure 8 Hamilton city Boundary Map

demonstrated on Figure 8. Figure 8 shows the Hamilton MBs considered for this study. There are 1030 MBs in total. The food and physical environments were overlaid on the Hamilton city boundary map. This provided a visual indication of the obesogenicity of areas in Hamilton, based on the characteristics of the food and physical environments.

5.4.2 Food environment

The food environment is defined in Chapter 4 of this research project as the geographic access to food sources within a given community, (Health Canada, 2013). The obesogenic food environment is a key focus point of this research project. These environments typically contain a high number of unhealthy food outlets, such as takeaways and dairies. This research method measured the food environment based on the number unhealthy of fast food outlets situated within the home, route and school environments of the NZHS participants. Information provided by the Waikato District Council gave a list of every registered food outlet within Hamilton. There were a total of 866 registered food companies in Hamilton. The information was categorised into 24 different sections based on the type of food sold by the company, for example bakeries, dairies, takeaways etc. The name and address of the 866 food company were listed in the WDC data. The information was able to be geocoded using google maps geocoding API programme. This programme (designed and operated through google maps) allows written address points to be geographical identified on a map, (Google Maps, 2015). Using this technology, each food point was assigned latitude and longitude coordinates, allowing them to be plotted on ArcMap. The categorisation of these food companies was an important consideration in this research method. This study is interested in food outlets selling unhealthy food sources that children aged 5-14 would pass on their journey to and from school. There are many food companies that do not match this description. For example, 1 of the 24 sections categorised by the Waikato District Council

was greengrocers. These companies typically sell healthy food sources, such as fruit and vegetables. Therefore they are unlikely to contribute to an obesogenic environment, and can be eliminated from this study. Many food sources were not applicable in the context of a child's diet. Food companies such as private hospitals, rest homes, and sports halls are not publically available food sources, and were also able to be eliminated from this research method. Food sources such



as butcheries were able to be eliminated simply due to the unlikelihood that a child would independently purchase food from this source. Upon review, four categories were used in this study as the most likely food sources children would encounter on an average journey to school; Bakeries, Dairies, Takeaways, and Delis/Eating-houses. The Food environment used within this research method is shown on Figure 9

5.4.3 Physical Environment

The physical environment is defined in Chapter 4 of this research project as the built and physical aspects of an environment, (Jackson, 2003) The physical environment is a key determinant in how active individuals can be within a given urban area. Healthy physical environments are areas that allow residents to be physically active as they interact in their surroundings. Obesogenic environments are characterised by a lack of access to avenues of physical activity, such as a lack of walkability and greenspace. This research method measured the physical environment by the amount of greenspace situated within the home, food and school environment of the NZHS participants. The greenspace data used from this research method was accessed from Koordinates.com, which contained a shape file showing all land coverage in New Zealand. The spatial data was edited in ArcMap to only show urban greenspace in New Zealand. This shape file was then reduced to fit the Hamilton boundary map by using the clip edit tool in ArcMap. The resulting physical environment is shown on Figure 10. The food and physical environment were both overlaid onto the original Hamilton boundary map. This provides a visual indicator of areas in Hamilton characterised as obesogenic environments. Areas with a high number of unhealthy

food outlets and a lack of greenspace would typically indicate an obesogenic environment. The next step in the Hamilton city geospatial method was to establish home, route and school environment of the NZHS participants.

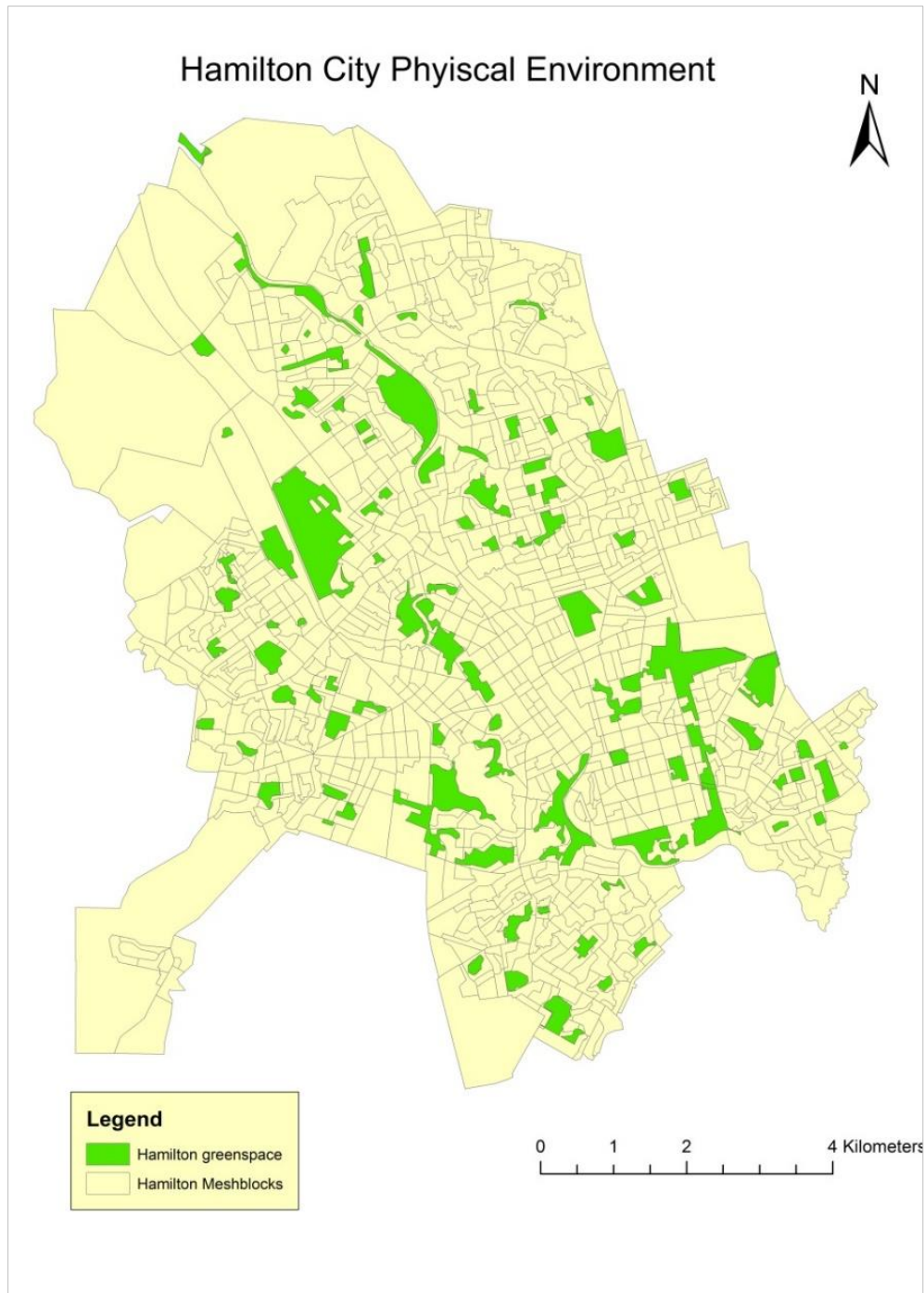


Figure 10 Hamilton City Physical Environment: Greenspace

5.4.4 Creating the Participant's Environment

There were 70 children used within the Hamilton city geospatial analysis. The same NZHS variables used in Part 1 (the nationwide analysis) were used for Part 2. The MOH was able to identify NZHS children aged 5-14 in Hamilton. The safety and privacy of the NZHS participants was again an important consideration. Part 2 of the research is focused on a smaller geographic scale to Part 1. The nationwide analysis considered NZHS participants nationwide, as opposed to Hamilton city geospatial analysis. This increases the risk of identification for Hamilton NZHS participants. Part 2 of the research method is focusing on school children in Hamilton (aged 5-14). There are three aspects of the participant's environments that were measured in this research method: the home, route and school environment.

Home environment - The surrounding area that the NZHS participant lives in.

Route environment - The most likely route the NZHS participant will take to get to and from school.

School environment – the most likely school the NZHS participant will attend.

In order to identify the geospatial characteristics of the participant's environment, some assumptions were made about the participant's route and school environments. The home environment is the only certain geospatial attribute known by the MOH about the participant (the participants MB). The NZHS does not state which school the participant attends in Hamilton, therefore the school environment of the child is unknown. As the participant's school is unknown, the route environment of the participant is also unclear, as there is no way to indefinitely match the home and school environment of the NZHS participants. As the route and school environment of the NZHS participants were not available, geospatial methods using GIS were used to determine the most likely route that the participant will take on their journey to their predicted school. As

was the case in previous research, distance was the key consideration in route GIS modelling. This research assumes participants will attend the school closest to the participant's home. In the case of this method, the home environment was identified by participants MB. The physical address of the participant was not recorded in the NZHS questions, as it would be highly unethical to do so. In order to better predict the location of the participants, each NZHS MB was assigned a Population Weighted Centroid (PWC). A centroid was created for each NZHS MB using a pre-existing data set designed by the University of Canterbury Geo Health laboratory. The participant's most likely route to school was determined using a closest facility network analysis. This research assumes that the participant will attend the closest school to the participants PWC. The closest facility network analysis was used to identify the shortest route from the PWC to the closest school. The school data points for this research were acquired from online source Koordinates.com, which used a Zenbu open source data set for New Zealand schools, (Zenbu, 2011). This data set provided a list of all New Zealand contributing primary, full primary, intermediate and secondary schools. The clip tool was used in ArcMap to reduce the data set to match the Hamilton Boundary Map. In total, 48 Hamilton schools were used in the research method. The full list of all the schools used in this study is shown in Appendix 2.

The NZOGPS road network layer was used as a network within this analysis. The NZOGPS nationwide road network incorporates all New Zealand roads, and was supplied by the University of Canterbury Geo Health laboratory, (Geo Health, 2015) . As Part 2 of this research method was only tested in Hamilton, the road network was able to be reduced using the clip edit tool to match the Hamilton city boundary map. The results of the closest facility analysis show the closest route between the PWC and nearest school, which identified the route and school environments of participants. This process was repeated for all the 1030 MBs shown on the Hamilton city boundary

map Figure 8. Once all the PWC in Hamilton were matched to the closest school, the GIS map was sent to the MOH, who in turn identified the home, route and school environments of children aged 5-14 sampled in the NZHS. This ensured that the privacy of the participants is safe, as the NZHS participants MBs remains unknown to this researcher.

Although it is impossible to know for certain which school the NZHS participants attended, the NZHS and geospatial data available can help to reduce the amount of assumptions made about the route and school environment. Based on the information known about the NZHS participants, the closest network analysis can be controlled to ensure that children are attending a school that matches the appropriate age and sex of the child. The age of the participants will influence what school they will attend. There were four school types considered within this study: contributing primary, full primary, intermediate and secondary schools. Children aged 5-9 are only able to attend full and contributing primary schools. Children aged 10-13 could attend any of the four types. Children aged 14 could only attend a secondary school. These age groups were used as a guide in the closest facility network to ensure that the participant was matched with an age appropriate school. Schools that did not match the age criteria of the participants were used at network blocks. The closest facility is unable to send participants to blocked schools, and will find the closest school that matches the age requirements of the school with the age of the participant. The same process was done for the gender of the participants. Selected schools in this research project (particularly secondary schools) are single sex schools. Network blocks were used again to ensure that participants were sent to a gender appropriate school. Now that the participant's school is controlled for age and gender, this research method can reduce the number of assumptions made about the route and school environment.

5.5 Measuring the participants environment

Thus far, the food and physical environments of Hamilton have been created using ArcMap. The home, route and school environment for the 70 participants identified for the Hamilton children sampled from the NZHS. The next step is to identify the obesogenicity of the surrounding environment. This was achieved by measuring the participant's exposure to the food and physical environment. In the case of this research method, the food environment is the number of unhealthy food outlets. The physical environment is the amount of greenspace. Exposure was measured by number of unhealthy food outlets and amount of greenspace present within the home, route and school environments of the participant. The buffer tool was used in ArcMap to identify buffer zones around the home, route and school environments of the participants. Buffers are used in GIS to show an area of geospatial influence. In the context of this research method, the buffer zone will determine the participant's exposure to food and physical environments in Hamilton. The home environment is determined by the PWC of the NZHS participants. A 200 meter euclidean buffer zone was created around each participant's home environment. The 200 meter buffer zone was used with reference to previous research, as was mentioned in chapter 4. The route environment is determined by the most closest facility networks route output. A 30 meter euclidean buffer zones was created around the participant's route to school. This accounts for unhealthy food outlets on either side of the road network. The school environment is determined by the school the participants attend based on the outcome of the closest facility analysis. A 200 meter euclidean buffer zone created around the outside of the selected schools. Once again, the 200 meter buffer zone was referenced in previous research, as mentioned in chapter 4. A

hypothetical example of the home, route and school environment buffer zones is demonstrated by Figure 11.

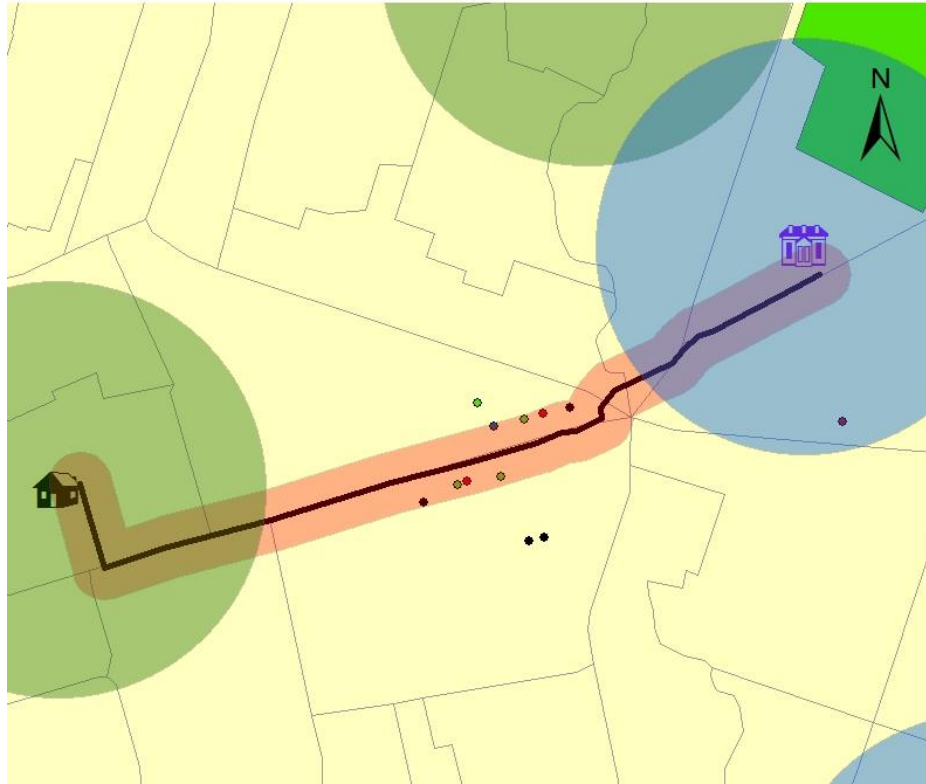


Figure 11 Home, Route and School Environment buffer zones example

The buffer zones created around the home, route and school environments represent the Hamilton food and physical environments area of exposure for participants. The food environment is measured by the number of unhealthy food outlets point features contained within the home, route and school buffer zones. These processes were completed by creating a new count field in the unhealthy food outlets attribute table. The field calculator was used to assign each count value 1. A spatial join was then created between a point feature shape file (unhealthy food outlets) and polygon feature shape (home, route and school buffer zones), while ensuring to indicate each polygon be given a summary of the numeric attribute. This process gave a count of the total

number of unhealthy food outlets within each participant's buffer zone. This number of unhealthy food outlets was used as the participant's exposure level to the food environment.

The physical environment was measured by the amount of greenspace contained within the home, route and school environments of the participants. The spatial intersect tool was used to calculate a polygon output, showing the area of greenspace contained within the participants buffer zones. The new area field column was created for the polygon output attribute table, using a field calculator to calculate the area of the output polygon within the buffer zones, which represents the amount of greenspace within the participant's home, route and school environment. The amount of greenspace (per square meter) will indicate the participant's exposure to the physical environment.

Each NZHS participant now has numeric value indicating their level of exposure to both the food and physical environments in Hamilton. The food environment is measured by the number of fast food outlets within each participant's buffer zone. The physical environment is measured by the amount of greenspace coverage represented in each participant's buffer zone. These processes ensured that all the relevant information about the participants of this research method had been determined, and was ready for analysis. The final step in the process was to remove all geographic information for the data set created for this GIS method. Each NZHS participants in Hamilton had their MB ID removed and were given random 8 digit values. This researcher was unable to access any of the geospatial sources of information, such as maps that would visually identify any aspects of the home, route and school environment buffer zones. The information sent back from the MOH was contained within a Microsoft Excel File. This data set contained the NZHS participant's data variables, and the food and physical environment exposure indices described above. No

geospatial information about the participants was given. This ensured the privacy of the NZHS participants is maintained.

5.6 Hamilton City Analysis Summary

The key objective of this analysis was to determine the connection between food and physical environments and the BMI status of Hamilton NZHS participants. This was investigated by using linear regression analysis in SPSS statistics. Two regression models were run to determine the correlation between BMI and both the food and physical environments of the participants. These regression models used BMI as the dependent variable in both regression models. The first regression model measured the food environment by the number of unhealthy food outlets contained within home, route and school environment buffer zone of the participants. The second regression model measured the physical environment by amount of greenspace (meters squared) contained within the home, route and school environment buffer zones of the participants. The purpose of this regression analysis was to determine if there is any geospatial correlation between the participant's environments and their BMI status. Both of the regression analysis models used the participant's age as a control. Age has been established as a strong predictor of BMI. The observed change between the two models when controlling for age provides a point of reference in analysis, and will indicate whether the participant's environment is contributing to BMI.

Chapter 6 Nationwide Results

The following chapter will demonstrate the results from the nationwide analysis of the NZHS participants. The following results included the total sample of children aged 5 to 14 from NZHS (2404 participants). It is important to analyse the demographic indicators of the participants (children aged 5-14) used in the nationwide population sample. As was mentioned in the method of the research project, a number of NZHS children aged 5-14 were eliminated from this study, as there was an insufficient amount of data for the child to participate in the study, (i.e. no BMI status). The demographics of the population sample were therefore an important focus in the nationwide analysis and results section of this research project, in order to determine the factors of age, social deprivation, transport mode and ethnicity impact BMI within this research projects population sample. This following chapter shows the results of this analysis.

6.1 Nationwide Children Mean BMI

The following graph represents the mean BMI of children sampled within this research. The BMI mean average was calculated for each age group, (5-14).

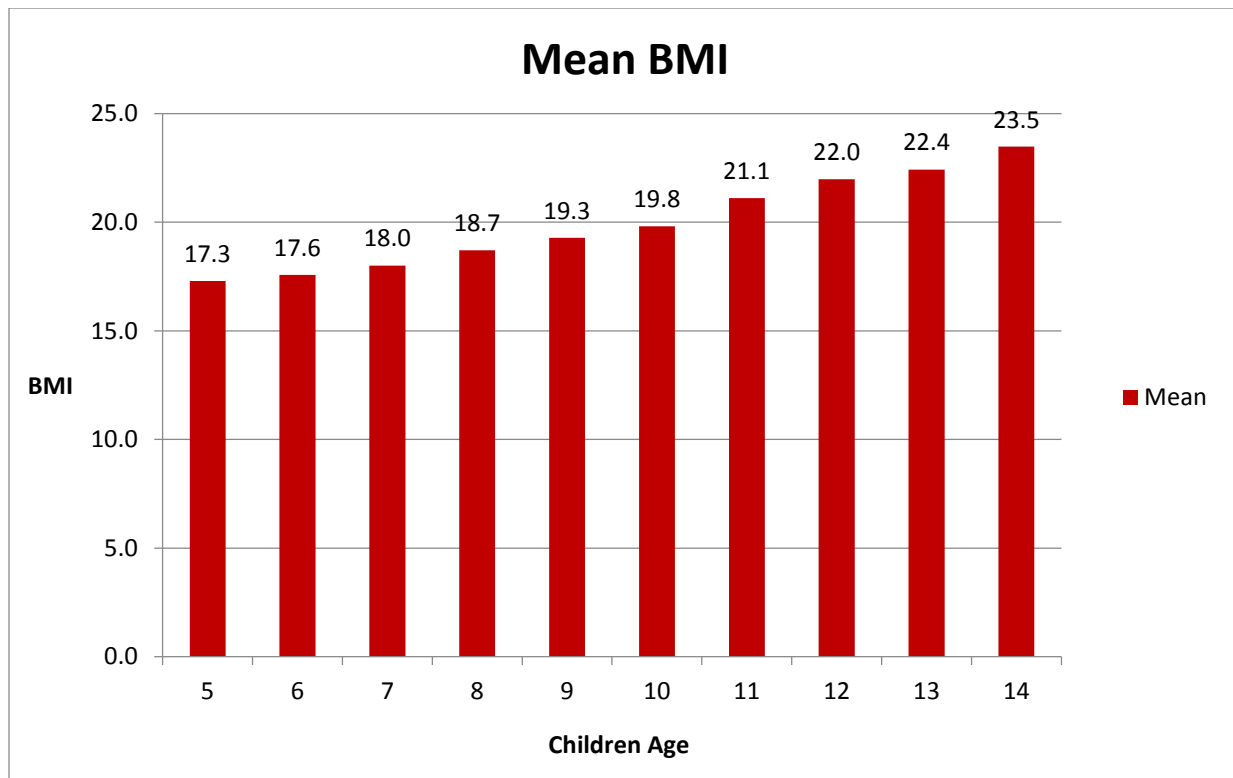


Figure 12 Nationwide Mean BMI per age group

The key finding from this graph is the connection between age and mean BMI. This graph shows that as age increases, the average BMI does the same. This increase shows the importance of age in the BMI calculation. The BMI method does not correct for age, which is one of the key limitations for using the BMI calculation. For example the average BMI for a child aged 5 is 17.3. This is significantly lower than average BMI for a child aged 14, which is 23.5. Age will therefore be an important control variable in the following results produced for the purpose of this study.

6.2 Nationwide BMI and Social Deprivation

The following results show the connection between BMI and Social Deprivation among the nationwide participants of this study. The relationship between BMI and social deprivation has already been referenced in chapter 4 of this research project as an important consideration. The correlation between mean BMI and social deprivation is demonstrated on Figure 14.

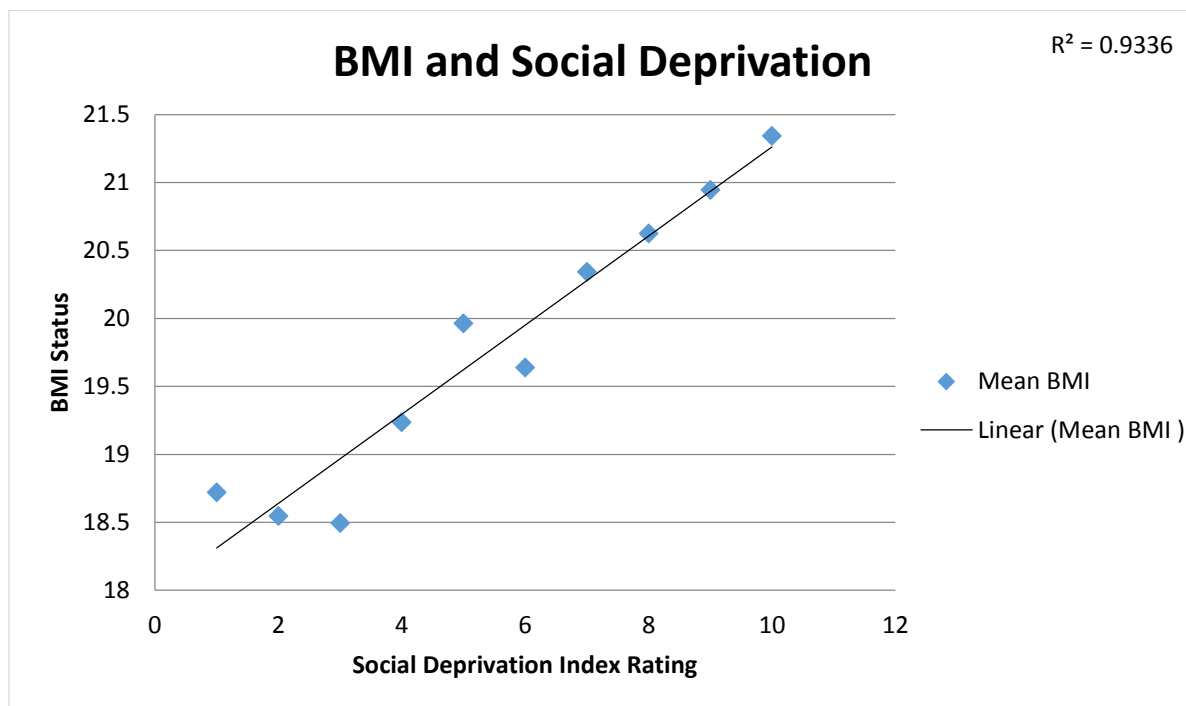


Figure 13 BMI and Social Deprivation

This graph shows the correlation between the area deprivation level of the participants MB and the participants average BMI. The mean BMI average was calculated for each social deprivation level given by the NZDep13 index; 1 being the least deprived areas and 10 being the most deprived. The graph shows a strong positive correlation between area deprivation level and BMI. The R squared value indicated on Figure 13 is 0.9336. This shows the data is close to fitting the linear (Mean BMI) regression line. This research project can report a significant positive correlation between BMI and social deprivation.

6.3 Nationwide Children Transport Mode

The mode of transport the participants uses to get and from school is an important consideration within this study. As was hypothesized, transport mode can be a factor in determining obesity exposure among school children. The following graph shows the number of children that used the modes of transport determined by the NZHS.

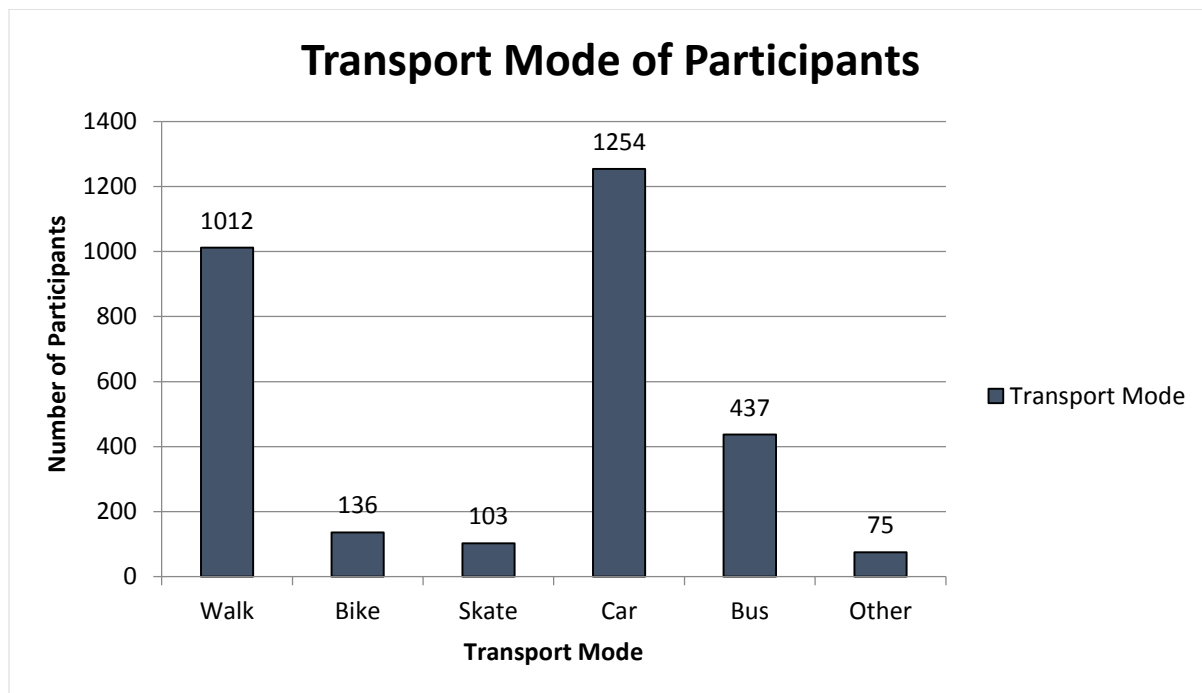


Figure 14 Nationwide Transport Modes of Participants

Walk, Bike and Skate are recognized as active modes of transport. Car and Bus are recognized as passive modes of transport. Figure 14 shows that walking (34%) and driving (42%) are clearly the most popular transport modes for children aged 5-14; both these transport modes represent 76% of the dataset. There is one important limitation to note from this graph. As is mentioned above, there were a total of 2404 children sampled for this study. However in the graph display above, the total number of children represented is 3017, which is a 25% increase from the original

sample number. The NZHS question that inquires about transport mode (C3.11) states that multiple responses are possible. Approximately 35% of children sampled for this study used more than one transport mode while travelling to and from school. In the case of children giving multiple responses for mode of transport, the NZHS values each transport mode equally. This makes it impossible to prioritize a specific mode of transport for children who gave multiple responses to the physical activity question.

Age is an important determinant of transport mode. 51% of children aged 5-9 were found to have been driven to school, (over half the population sample). However, 34% of children aged 10-14 were found to have been driven. The percent decrease in car use among children aged 10-14 was compensated primarily by walk (31% to 35%) and bus (8% to 16%). This suggests that older children are more likely to use transport independently, as opposed to younger children. Figure 15 represents mean BMI and transport mode on a bar chart.

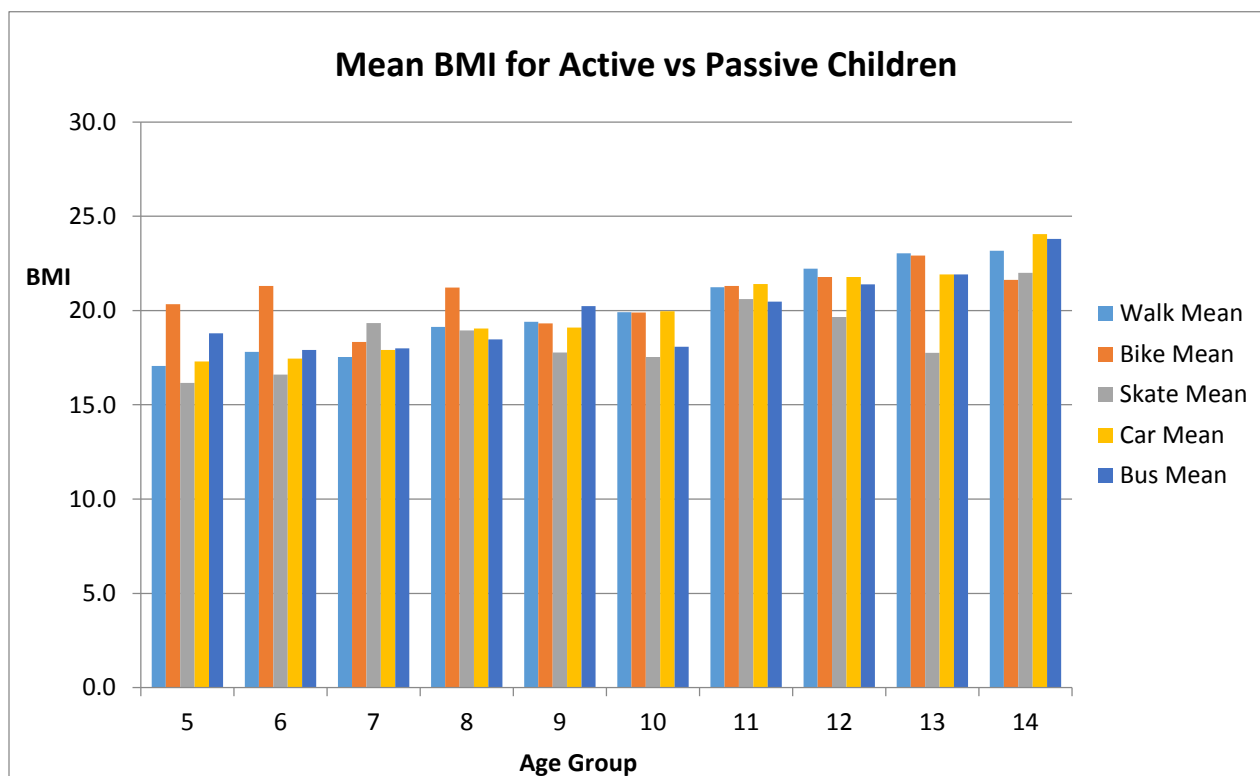


Figure 15 Nationwide Mean BMI for Mode of Transport

This graph shows the fluctuations that exist in Figure 15. The average BMI for children aged 5-8 who bike to school are significantly higher than other transport modes within this age grouping. This graph does not represent any significant connection between mean BMI and mode of transport. As expected, the BMI average increases as age increases, which has been previously established. The BMI average for walk, car and bus was 20. Skate had the lowest BMI average with 19. Bike had the highest BMI average with 21. It is important to consider the limited number of children that skate and bike to school, which did not represent an accurate reflection due to a lack of sample size.

6.3.1 Transport Mode Regression analysis

The following section used a linear regression analysis to determine the connection between the participants BMI and their mode of transport. BMI was used as the dependent variable in this linear regression analysis. Transport mode was used as the independent variable. The results of this regression analysis will hope to determinant if transport mode contributes to BMI status. The R squared results of the linear analysis are shown on Table 2.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F
Walk	.048 ^a	0.002	0.002	4.833	0.002	5.494	1	2401	0.019
Bike	.040 ^a	0.002	0.001	4.835	0.002	3.892	1	2401	0.049
Skate	.057 ^a	0.003	0.003	4.831	0.003	7.953	1	2401	0.005
Car	.104 ^a	0.011	0.01	4.812	0.011	26.462	1	2401	0
Bus	.084 ^a	0.007	0.007	4.822	0.007	17.248	1	2401	0

Table 2 BMI vs Mode of Transport Regression Analysis Mode Summary

The R squared values of Table 2 suggests that the model does very little to explain the correlation between BMI and mode of transport. Car has the highest R squared value of 0.011, which is still

statistically insignificant, explaining very little about the variation of the data set. However Sig. F shows a statistically significant relationship between BMI and all the modes of transport. Bike is the least noteworthy with Sig. F of 0.049; however this value is still low enough to be considered statistically significant in the context of this regression model. The coefficient results of the regression analysis between BMI and mode of transport are demonstrated in Table 3.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.F	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
Walk	(Constant)	19.854	.130		153.202	0.000	19.600	20.108
	Walk	.468	.200	.048	2.344	.019	.076	.860
Bike	(Constant)	20.004	.102		196.988	0.000	19.804	20.203
	Bike	.842	.427	.040	1.973	.049	.005	1.679
Skate	(Constant)	20.110	.101		199.641	0.000	19.912	20.308
	Skate	-1.372	.487	-.057	-2.820	.005	-2.326	-.418
Car	(Constant)	20.579	.142		144.949	0.000	20.300	20.857
	Car	-1.011	.197	-.104	-5.144	.000	-1.396	-.626
Bus	(Constant)	19.859	.109		182.621	0.000	19.645	20.072
	Bus	1.059	.255	.084	4.153	.000	.559	1.559

Table 3 BMI vs Mode of Transport Regression Analysis Coefficients Table

The unstandardized coefficient column labelled B shows the predicted change in BMI based on the mode of transport the participant uses to get to and from school. Table 3 shows a positive correlation between BMI and walk, bike and bus transport modes. Bus is shown to have the strongest correlation, showing a 1.059 average increase in the BMI of the participants who used the bus to get to school. Bike and walk shows lower rates of increase in BMI, at 0.842 and 0.468 respectively. Table 3 showed a negative correlation between BMI and the car and skate transport

modes. Skate transport mode demonstrated a -1.372 average decrease in BMI per unit. Car transport was marginally less, showing a -1.011 average decrease in BMI.

6.4 Nationwide Analysis of Passive Transport vs Active Transport

The following results section will analyse the BMI outcomes in regards to active transport modes versus passive transport mode. The NZHS data displayed six gave transport modes that children use to travel to and from school: walk, bike, skate, car, bus, public transport and other. For the purposes of this section, other was excluded from the analysis, as the majority of NZHS participants did not state what alternative transport they used. As was the case in the nationwide transport mode results, bus and public transport were combined together. Walk, bike and skate are active forms of transport; car and bus are passive forms of transport. Children who use active transport to school are expected to have a lower BMI, given their increased level of physical activity. The Mean BMI per age group for exclusively active and passive transport is expressed in Figure 16. The mean BMI of all participants was included as a control.

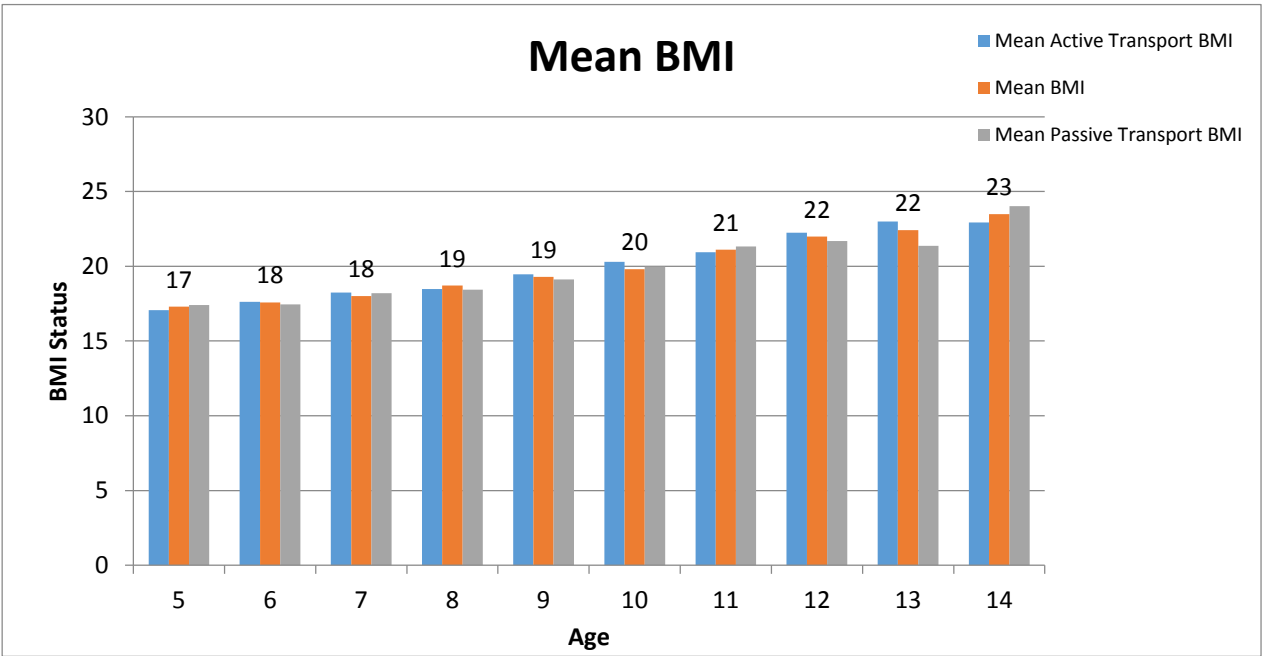


Figure 16 Mean BMI for Active vs Passive Participants

Figure 16 indicates that there is no significant difference in the BMI status between exclusively active and passive transport modes and the mean BMI of the total population. There does not appear to be any significant relationship between BMI and exclusively passive and active transport modes. As was mentioned above, NZHS participants were permitted to give multiple responses of mode of transport. In total, 467 participants used both active and passive forms of transportation to and from school. They were not considered in the active vs passive transport analysis. 751 participants used exclusively active modes of transport. 1186 participants used exclusively passive modes of transport, giving a total of 1937 participants considered for the active vs passive transport mode analysis. Mean BMI, age and social deprivation was calculated in the analysis of Active vs Passive transport mode. The results are displayed on Table 4

Table 4 NZHS exclusively active vs exclusively passive participants information

	Active Transport	Passive Transport	Total Sample
Number of Participants	751	1186	1937
Mean BMI	20.4	19.8	19.1
Mean Age	10.0	9.3	9.3
Mean Social Deprivation	6.8	6.3	6.3

6.4.1 Mean BMI

The mean BMI for the total sample of exclusively active and passive participants was 19.3. Both the exclusively active and passive participants were found to have mean BMIs higher than the mean BMI of the total sample. The mean for exclusively active transport participants was 20.4. This was only marginally higher than the Mean BMI of the exclusively passive participants of 19.8. The difference between the BMI of exclusively active and exclusively passive participants

is not enough to indicate a trend. This would suggest that the use of active transport does not have a significant effect of their BMI status.

6.4.2 Age

The mean age of the total sample of exclusively active and passive participants was 9.3 years old. The mean of the participants who used exclusively passive modes of transport was 9.3 years, identical to the mean age of the total sample. The mean age of exclusively active participants was 10 years old, 0.7 years older than the mean age of the total sample. This increase shows that older participants were more likely to use exclusively active transport. This can potentially lead to an overrepresentation in the mean BMI status of participants who used exclusively active transport. It was established in the nationwide children's statistics results that BMI incrementally increases with age. Exclusively active participants are therefore more likely have a higher BMI based on a higher mean age than exclusively passive participants. When this is considered, it appears age has not significantly contributed in the BMI between exclusive active and passive transport modes.

6.4.3 Mean Social Deprivation

The Mean Social Deprivation for the exclusively active transport participants was 0.5 higher (6.8) than exclusively passive participants (6.3). This could suggest that exclusively active participants live in areas of higher deprivation compared to participants who use exclusively passive transport modes. This relationship reflects the socioeconomic variables that were considered in the creation of the NZDep13 index. The two transport modes used by exclusively passive participants were car and bus. Car ownership was one of the census variables used for the deprivation index. Participants in highly deprived areas are less likely to use or own cars. Active transport such as walking, biking and skating is a low cost mode of transportation to and from school. This

theoretically explains why exclusively active participants are more likely to live in socially deprived areas. Social Deprivation will be considered within the geospatial analysis of Hamilton City. This research project predicted participants that use exclusively active mode of transport would have a lower BMI status than participants that use exclusively passive modes of transport. The results of this analysis suggest this is not the case. Exclusively active and passive modes of transport have no determinant in the outcome of BMI on a nationwide scale.

6.6 Nationwide Children Ethnicity Mode

Ethnicity was considered within the active vs passive analysis. This research project has already alluded to the connection between BMI and ethnicity in the context of New Zealand obesity. Figure 17 show the different ethnicities of the NZHS participants selected for the nationwide analysis.

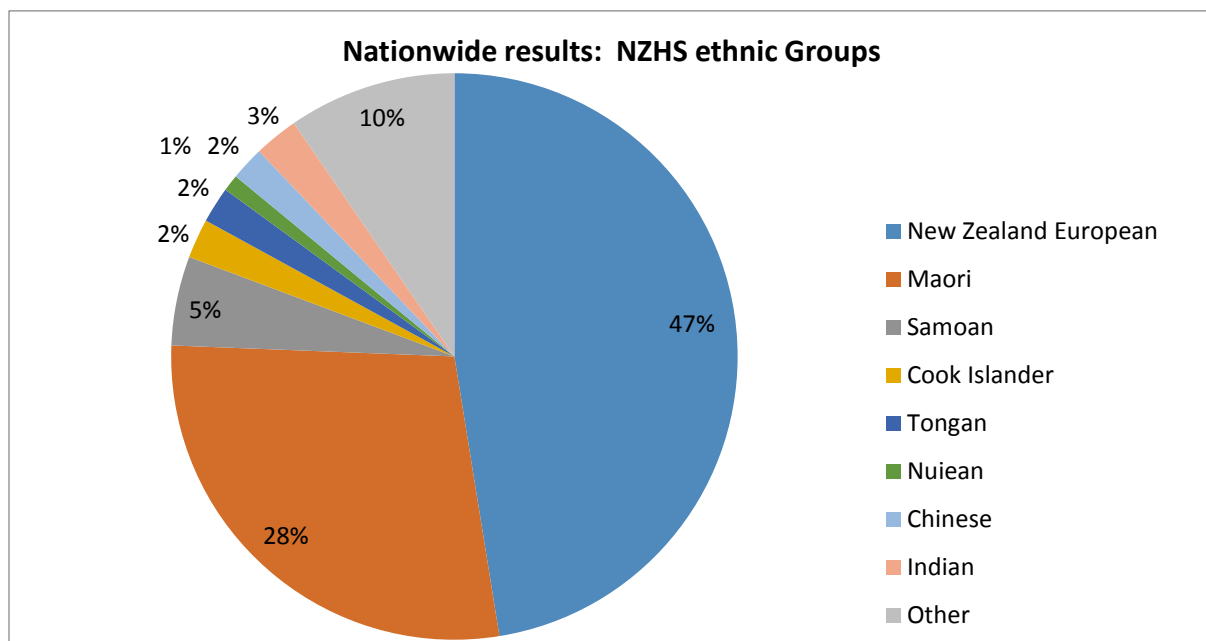


Figure 17 Nationwide Proportion of NZHS Ethnic groups

New Zealand European is the highest represented ethnicity (47%). Maori and Samoa are next highest one 28% and 10% respectively. The remaining ethnicities represent a small proportion of

the nationwide population sample, all 5% or less. Figure 19 shows the mean BMI of each ethnic group sampled in the nationwide analysis. Other was excluded from the graph as the ethnicities of these participants were unidentified.

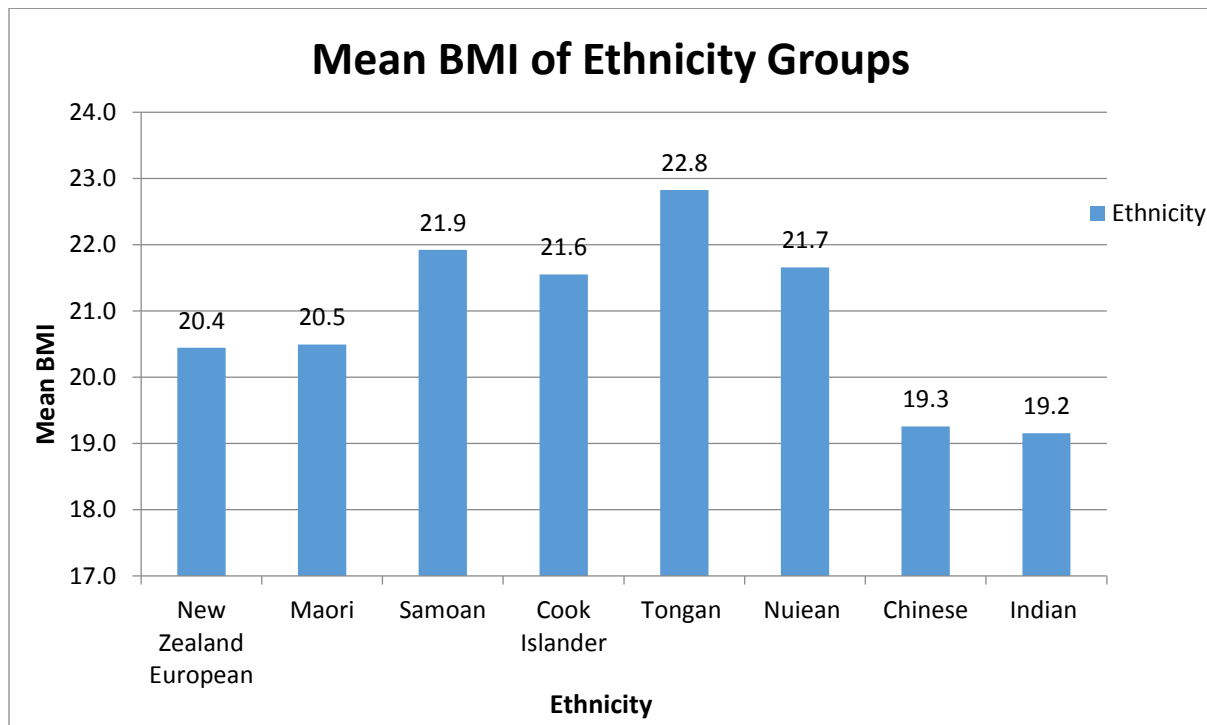


Figure 18 Nationwide Mean BMI of NZHS Ethnic Groups

Figure 18 shows Tongan has the highest mean BMI across the different ethnicities at 22.8. Cook Island, Samoan and Niuean ethnicities are also strongly represented, all showing a mean BMI of over 21. These ethnicities are classified under the NZHS as Pacific Island, who are strongly represented in childhood obesity statistics within New Zealand. The mean BMI of the Maori was an unexpected result from this analysis. Chapter 4 of this research project stated that Maori childhood obesity rates were second highest of the sampled ethnicities in the NZHS. However, figure 19 shows the mean BMI for Maori is virtually identical to New Zealand European at 20.5, well below the Pacific Island ethnicities.

6.7 Nationwide Results Summary

The results of the nationwide analysis failed to determine any significant connection between the participants BMI and mode of transport. Despite table 3 showing the regression results were statistically significant, the low R squared values for each mode of transport sampled (walk, bike, skate, car and bus) suggests the regression model does little to explain any significant correlation between BMI and mode of transport. The most significant results of the nationwide analysis proved to be the connection between the social indicators of age, ethnicity and social deprivation. Age was found to be important indicator of BMI, showing that BMI increases with age. The ethnicity analysis results showed the average BMI for Pacific Island ethnicities (particularly Samoan and Tongan) were noticeable higher than the other ethnic groups sampled within the study. Social deprivation was also observed as a strong predictor of BMI status among NZHS participants. Figure 13 showed a strong correlation between the participants average BMI per age and level of social deprivation as determined by the NZDep13 index. These social indicators proved be very effective predictors of BMI, and yielded results far more significant than regression analysis between participants BMI and mode of transport.

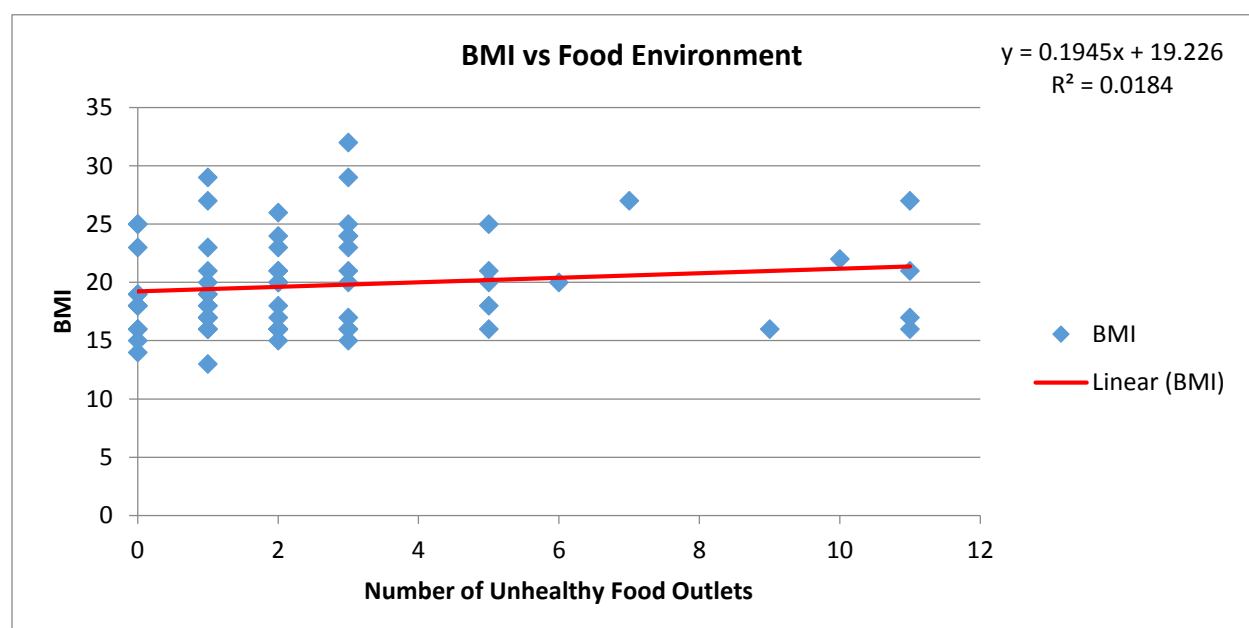
6.8 Part 2 Result - Hamilton City Geospatial Analysis

The following section shows the results of the Hamilton city geospatial analysis. This analysis used linear regression models created in SPSS statistics. These regression models were used to determine if a geospatial relationship exists between the food and physical environments exposure and BMI status. The following shows the results of this analysis.

6.9 BMI vs Food Environment

This section reports the analysis results between BMI level of Hamilton participants and the surrounding food and physical environments. A linear regression analysis model was used to investigate the statistical significance of the relationship between BMI and environment. BMI was used as the dependent variable in the regression model, and the food and physical environments of the participants were used as independent variables. The food environment was measured by the number of unhealthy food outlets within a participant's buffer environment. The Model Summary results of regression analysis between BMI and the food environment are displayed below.

Table 5 BMI vs Food Environment Scatterplot Graph



The results indicated on Table 5 show a minor positive correlation between the food environment and BMI status of participants. Participants with a higher BMI have more unhealthy food outlets within their exposure area, suggesting a small relationship between BMI and number of unhealthy food outlets. The positive correlation is too minimal to be considered statistically significant. Table 5 shows an R square value of 0.018. This low R squared value does not allow any significant conclusions to be drawn from table 5. This analysis also used an anova regression model to represent the correlation between participant BMI and the food environment. The key purpose of this model was to test the statistical significance of the relationship between BMI and the food environments. The results of the anova regression analysis are displayed on Table 6.

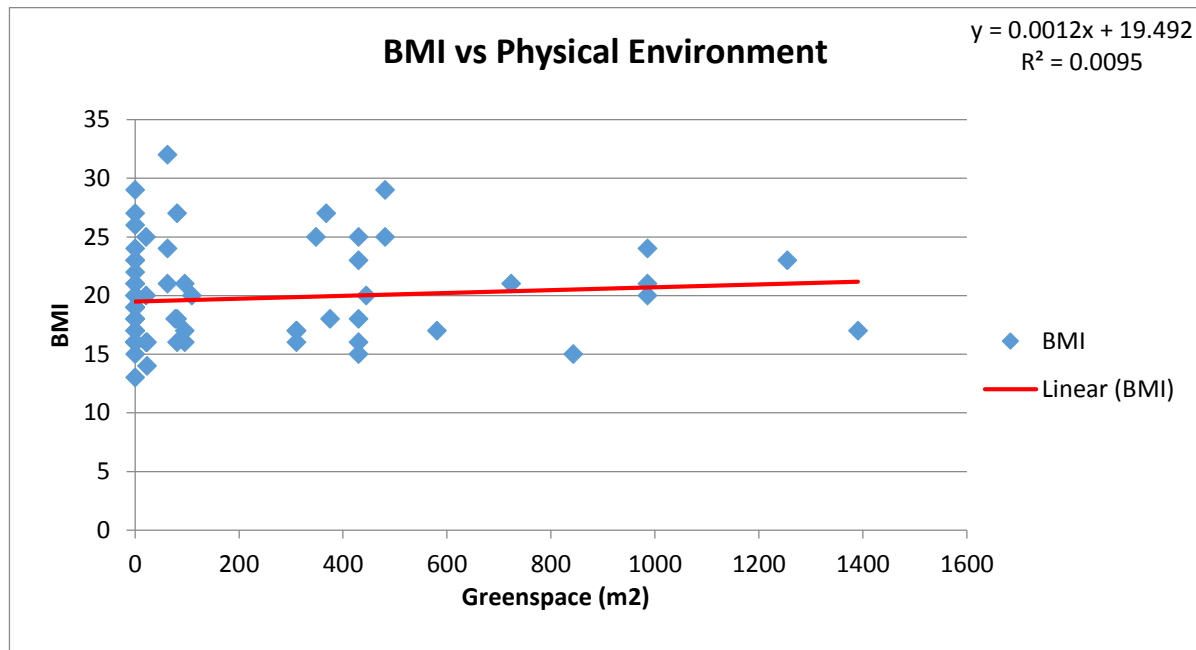
Table 6 BMI vs Food Environment Anova Results Table

ANOVA^a			
Model	Sum of Squares	Mean Square	Sig.
Regression	19.763	19.763	.284 ^b
Residual	1153.608	16.965	
Total	1173.371		
a. Dependent Variable: BMI			
b. Predictors: (Constant), Food Environment			

The most important finding from Table 6 is the level of statistical significance (Sig), which is shown to be 0.284. This Sig. value suggests the relationship between BMI and the food environment is not statistically significant. It is well above 0.05, which is recognized as the minimum value required to indicate statistical significance in an anova model. Based on the regression results from tables 5 and 6, this research can conclude there is no significant relationship between the BMI of the Hamilton participants and the surrounding food environment. The following regression results test the correlation between BMI and the physical environment. The physical environment was measured by the amount of greenspace within a participant's buffer

environment. The Model Summary results of the regression analysis between BMI and the physical environment are displayed on Table 7.

Table 7 BMI vs Physical Environment Scatterplot Graph



The results indicated on Table 7 do not show any statistically significant correlation between BMI and the physical environment. There is a minor positive relationship between greenspace exposure and BMI outcomes, which is evidenced by the increasing linear (BMI) trend line. Similar to Table 5, the R squared values in Table 7 are too low to indicate a statistically significant correlation. An anova regression was also used to measure the statistical significance between participant BMI and the physical environment. The results of the anova model are displayed on Table 8 below.

Table 8 BMI vs Physical Environment Anova Regression Table Results

ANOVA^a			
Model	Sum of Squares	Mean Square	Sig.
Regression	1	0.651	.423 ^b
Residual	68		
Total	69		
a. Dependent Variable: BMI			
b. Predictors: (Constant), Greenspace30m			

Table 8 shows little statistical significance in the regression analysis results. The Sig. value shown on the Anova table is 0.423, which is too high to be considered statistically significant. Both table 5 and 7 shown for the regression analysis between BMI and physical environment have failed to identify any significant correlation. The results of the linear regression analysis suggest that no correlation exists between BMI and the physical environment.

6.10 BMI and the environment controlled for age

Age was used as a control in the second stage of the regression analysis between environment and BMI. The nationwide results of this research project have already demonstrated that age is an important determinant in BMI. For this reason, age was used as a control for the second stage of the regression analysis. The same regression models demonstrated above were ran again, this time incorporating age as an independent variable within the analysis. The observed change in the results between the two stages of regression analysis is shown below. Table 9 shows the results of the regression analysis between the dependent variable of BMI and the independent variables of the food environment and age.

Table 9 BMI vs Food Environment (controlled for age) Regression Model Summary

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.549 ^a	.301	.280	3.498
a. Predictors: (Constant), Food Environment, Age				

The results of Table 9 indicate important differences in comparison to Table 5. The most notable change is the increase in the R squared value. When aged is incorporated into regression analysis, the R squared value increases from 0.002 to 0.310. This improves the quality of the regression model significantly.

Table 10 BMI vs Food Environment (controlled for age) Anova Results Table

ANOVA ^a						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	353.363	2	176.682	14.436	.000 ^b
	Residual	820.008	67	12.239		
	Total	1173.371	69			
a. Dependent Variable: BMI						
b. Predictors: (Constant), Age, Food Environment						

The results of the Anova table show the Sig. value has decreased from 0.284 to 0.000. This shows that the introduction of age made the regression results statistically significant, something that was not evident in the original regression model between BMI and food environment. By controlling for age, the regression results are now considered more statistically significant. Table 11 shows the results of the regression analysis between the dependent variable of BMI and the independent variables of the physical environment and age.

Table 11 BMI vs Physical Environment (controlled for age) Regression Model Summary

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.548 ^a	.300	.279	3.501
a. Predictors: (Constant), Greenspace, Age				

As was the case in the regression model between BMI and the food environment, using age as control has increased the R squared value, from -0.001 to 0.300.

Table 12 BMI vs Physical Environment (controlled for age) Anova Results Table

ANOVA^a			
Model	Sum of Squares	Mean Square	Sig.
Regression	2	14.359	.000 ^b
Residual	67		
Total	69		
a. Dependent Variable: BMI			
b. Predictors: (Constant), Age, Greenspace			

The results of the anova model in table 12 show the Sig. Value of the regression model has decreased from the 0.423 in the original anova table to 0.000 when controlling for age. This shows the regression model has become statistically significant, which was not the case in the original regression analysis between BMI and the physical environment. The use of participant age as a control within the regression analysis acted to improve the R squared and Sig. Values of both regression models for the food and physical environments. The observed change in the statistical values for the regression model between BMI and both the food and physical environments demonstrated that age was an effective predictor of BMI. It also showed the lacking correlation between BMI and both the food and physical environment. The results of the regression analysis between participant BMI and the environment determined there was no correlation between these two variables. Therefore the surrounding food and physical environment of the Hamilton participants did not influence their BMI outcome.

6.11 Mode of Transportation and Environment

This section reports the connection between the Hamilton participant's mode of transport and the food and physical environment. This connection was analysed using a linear regression model.

The analysis ran two separate linear regression models. Table 13 used the food environment as the dependent variable and table 14 used the physical environment as the dependent variable. Both table 13 and table 14 measured the correlation between the environment and the five modes of transport used by Hamilton participants (walk, bike, skate, car and bus). The purpose of this analysis was to determine whether the food and physical environments of the Hamilton participants contributed to the mode of transport participants used. Age and BMI were used as controls in this regression analysis. The results of the regression analysis between the food environment and mode of transport are displayed below.

Table 13 Food Environment vs Mode of Transport (controlled for age and BMI) Regression Model Summary

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
Walk	.115 ^a	0.013	-0.001	2.875
Bike	.075 ^a	0.006	-0.009	2.886
Skate	.149 ^a	0.022	0.008	2.862
Car	.169 ^a	0.028	0.014	2.852
Bus	.119 ^a	0.014	0	2.873

a. Predictors: (Constant), Mode of Transport, Age, BMI

The results of the linear regression do not suggest any significant relationship between the participant's food environment and their mode of transport. This is evident by the low R squared value shown on table 13. Walk and bike transport modes have the lowest R squared values, at 0.013 and 0.006 respectively. Car was the most significant at 0.014. This R squared value is still too low to suggest any statistically relevant correlation between the food environment of the participants and their mode of transport. The use of age and BMI as a control in this model did not improve the significance of the findings. The results of the regression analysis between the physical environment and mode of transport are displayed below. Age and BMI were once again used as controls.

Table 14 Physical Environment vs Mode of Transport (controlled for age and BMI) Regression Model Summary

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
Walk	.260 ^a	.068	.054	3431
Bike	.358 ^a	.128	.115	3318
Skate	.047 ^a	.002	-.012	3549
Car	.079 ^a	.006	-.008	3542
Bus	.121 ^a	.015	.000	3527
a. Predictors: (Constant), Mode of Transport, Age, BMI				

The results of the regression analysis suggest that no significant correlation exists between the physical environment and mode of transport. Similar to the results of the food environment regression analysis, the R squared values are still too low to suggest any statistically significant correlation. Table 14 shows walk and bike have the highest R squared values at 0.068 and 0.128. Bike is the most significant of the five transport modes. This is still too low to indicate a meaningful correlation between participants that bike and the physical environment.

6.12 Nutrition and Environment

The following section shows the results of the linear regression analysis between the food and physical environment and the nutrition intake of NZHS Hamilton participants. The nutrition intake section in the NZHS indicates the number of servings per week for 4 different food types: fizzy drinks, takeaways, vegetables and fruit. Fizzy and takeaways are examples of low nutrition food sources, and would typically be available in obesogenic environments. Vegetables and fruit are examples of high nutrition food sources, and would typically be available in healthy food environments. It is presumed that participants who live in obesogenic environments will consume a higher number of fizzy and takeaway products. The inverse is presumed for participants who live in non-obesogenic environments. This regression analysis asks if the Hamilton food and physical environment contributes to the amount of healthy or unhealthy food that participants

consume (based on the NZHS responses). The results of the linear regression analysis between the food and physical environment and the nutrition intake of Hamilton participants are demonstrated below. Age and BMI were used as controls in this linear regression analysis model. The following table shows the regression analysis results between the food environment and nutrition intake of Hamilton participants.

Table 15 Food Environment vs Nutritional Intake (controlled for age and BMI) Regression Model Summary

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
Fizzy	.169 ^a	.028	.014	2.852
Takeaway	.113 ^a	.013	-.002	2.875
Vegetables	.141 ^a	.020	.005	2.865
Fruit	.104 ^a	.011	-.004	2.878
a. Predictors: (Constant), NZHS Nutrition, Age, BMI				

Table 15 shows very little correlation between the food environment and nutrition intake. This is evidenced by the low R squared values, none of which suggest the model is statistically significant. There is also no significant difference between the R squared values of low nutrition food sources (fizzy and takeaway) and the high nutrition food sources (vegetables and fruit). These results suggest the food environment of the Hamilton participants is not contributing to the level of nutrition intake, both for unhealthy and healthy food sources. The following table shows the regression analysis results between the food environment and nutrition intake of Hamilton participants.

Table 16 Physical Environment vs Nutritional Intake (controlled for age and BMI) Regression Model Summary

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
Fizzy	.086 ^a	.007	-.007	3540
Takeaway	.031 ^a	.001	-.014	3551
Vegetable	.043 ^a	.002	-.013	3550
Fruit	.183 ^a	.033	.019	3493

a. Predictors: (Constant), NZHS Nutrition, Age, BMI

The results table show very little correlation between the food environment and nutrition intake. This is showed by the low R squared values, none of which suggest the model is statistically significant. The R squared values are even lower than the result from the food environment regression analysis, suggesting the physical environment is even less significant in contributing to nutrition intake. Once again, there was no significant difference in the R squared values of the low nutrition and high nutrition value of participants. The results of this regression analysis suggest the physical environment is not contributing to the nutrition intake of Hamilton participants.

6.13 Hamilton Geospatial Results Summary

The purpose of the Hamilton geospatial analysis was to determine if the food and physical environment of Hamilton contributed to any of the participants health outcomes recorded in the NZHS. The results of this analysis can conclude that no meaningful geospatial relationship was established between the participant's environment and any of the NZHS variables that were tested in the linear regression analyses. The results of this research method suggest that the environment that NZHS participants are exposed to do not directly contribute to BMI. The following results will be further explored in the proceeding discussion chapter of this research project.

Chapter 7 Discussion

Summary

7.1 Key Findings

This section will discuss the key findings from the results of both the nationwide and Hamilton analysis of NZHS children aged 5-14 in this research project.

7.1.1 Nationwide Key Findings

The nationwide analysis of NZHS children did establish some key findings when comparing BMI to other selected variables from the NZHS. The three key variables discussed were age, social deprivation and ethnicity. These three NZHS variables were shown to have significant implications on BMI status in the nationwide analysis. The increase in BMI relative to age was a predicted result. A key limitation to the BMI calculation is that age is not taken into account in the final BMI result. As children's height and weight increases, the BMI status of children increases accordingly. This increase can make it difficult when determining the weight status of NZHS participant, whether they be underweight, normal, overweight or obese. This research project attempted to measure obesity outcomes based on the BMI status of participants. There were 2404 children sampled in the nationwide analysis. The large population sample meant that an analysis of each participant's weight status relative to their age would both be time consuming and difficult to determine. Age was however used as control in all regression analysis. This was to ensure that ages influence on the BMI calculation was considered within the results of the regression analysis.

The participant's social deprivation was one of the most statistically significant indicators of obesity. The results from Figure 14 show a strong relationship between BMI and social deprivation. Nationwide participants that live in highly deprived areas are more likely to have higher BMI; the inverse is true for the least deprived areas. This is supported by an R squared value of 0.9336 shown on Figure 14. This demonstrates the data set fits within 90% of the true regression line, which suggests a statistically significant trend between increased BMI and social deprivation. Social deprivation was measured using NZDep13 index designed by the University of Otago. This index measured area deprivation of all MBs nationwide. Each NZHS participants was given a social deprivation level assigned by a data join between NZHS MBs and nationwide MBs in ArcMap. This index is a measure of area deprivation. The results from Figure 14 show that exposure to deprived areas can increase BMI.

Ethnicity is a key focal point in regards to obesity in New Zealand. Previous research by the MOH has pointed to the inequalities in obesity rates between different ethnicities in New Zealand. Pacific Island and Maori have been identified in Chapter 4 of this study as the most adversely affected ethnic groups. The results of the nationwide analysis show that Pacific Island ethnic groups (Cook Islanders, Tongan and Niuean in particular) had a higher mean BMI than the Maori, European and Asian ethnic groups. Maori was not represented as highly as expected in the nationwide sample, with a mean BMI only slightly higher than Europeans. Other than this, there were no unexpected findings within this analysis. Ethnicity is already well founded as a strong indicator of obesity exposure. It is for this reason that ethnicity was not used as a control in the linear regression analysis for the nationwide and Hamilton NZHS participants, as the connection between ethnicity and BMI has already been thoroughly considered within previous research into New Zealand obesity.

The linear regression analysis between BMI and mode of transport was the key analysis for the nationwide results section. This regression analysis aimed to test whether mode of transport to and from school had any influence on BMI status among nationwide NZHS participants. The results of the regression analysis demonstrated in table 3 show a positive relationship between the dependent variable (BMI) and the independent variables of walk, bike and bus. Table 3 indicates that participants who walk will have a 0.468 increase in BMI compared to the mean BMI of the nationwide sample. Participants who bike have a 0.842 increase in BMI compared to the nationwide sample. Participants that bus (which includes public transport) had the highest increase in BMI, of 1.059. This increase represents a positive correlation between participants that bike, walk and bus, and an increasing BMI level. The increase in BMI for walk and bike was referenced in Chapter 3. Despite walk and bike participants using active transport to get to and from school, their exposure was predicted to increase due to an ease of access to the food environment. The results of Table 3 support this expectation. However the results of the Hamilton geospatial analysis did not find any correlation between a participants mode of transport and obesogenic environments. Therefore this research project is able to state that walk and bike participants have a higher mean BMI than the total population sample, yet is unable to conclude that exposure to obesogenic environments is influencing this outcome.

Participants that used car and skate modes of transport were found to have lower BMI levels than the total population sample. Participants who drove to school had a -1.011 decrease in BMI; participants who skate to school had a -1.372 decrease in BMI. These modes of transport were both negatively correlated with increasing BMI status. The results of the car participants is consistent with the expected BMI outcomes for bike and walk. Children who drive to school are less exposed to obesogenic environment. The key reasons for this were also discussed in Chapter

3. Participants who are driven to school are less able to access unhealthy food outlets on their journey. Children aged 5-14 will be driven by a parent or caregiver, which will remove the option of stopping at an unhealthy food outlet. This could suggest that participants who drive are less exposed to obesogenic environments. Participants that skate were found to have -1.372 decrease in BMI compared to the total population sample. The skate option in the NZHS also includes 'other forms of physical activity' in the question on active transport. This suggests that participants that skate are the most physically active of all the transport modes sampled. This claim is supported by Figure 16, which shows skate participants have the lowest mean BMI in 7 of the 10 age groups sampled. The negative correlation between car and skate in regards to BMI are contradictory of each other. Car users were suggested to have lower BMI levels, as they are potentially shielded by their mode of transport and parental supervision. This by extension would suggest that skate participants would be exposed to obesogenic environments, as they are making the journey to school independently. However the results of Table 3 show both car and skate participants have lower BMI levels in regards to their mode of transport. This notion is supported by the imperceptible change in mean BMI for active and passive transport modes. This analysis considered exclusively active and exclusively passive participants from the nationwide population sample, measuring the difference between their mean BMI levels per age. The results shown on Figure 16 do not suggest any significant change in the mean BMI of active and passive transport modes. This finding is reflected in the results of the regression analysis. A mix of active and passive transports were correlated both positively and negatively with participant BMI. This makes it difficult to determine whether active or passive mode of transport contribute more to BMI. It is also important to consider the other statistical indicators given from the regression results between BMI and mode of transport. The R squared values for all modes of transport was very

low. This can suggest the strength of the model was not sufficient enough to indicate a trend, despite the positive and negative correlations found on table 3. This research project can conclude the participants that walked, biked and bused to school have higher mean BMI levels than the mean population sample. Skate and car participants have lower BMI levels than the mean population sample. The validity of this claim should be cautions as low R squared values make it hard to suggest any significant trend.

[Nationwide analysis discussion summary](#)

The results of the nationwide analysis show strong connections between BMI and the social indicators of age, social deprivation and ethnicity for participants. These variables represent significant trends on the New Zealand population, and should be carefully considered within obesity intervention in the future. The correlation between participant BMI and mode of transport was not significant enough to draw any meaningful conclusions. Using age as a control in the regression analysis improved the accuracy of the model, most notably the R squared and Sig value. The observed change in regression results when controlling for age allows us to state the mode of transport does not influence BMI.

[7.1.2 Hamilton Key Findings](#)

The key objective of the Hamilton geospatial analysis was to determine whether aspects of the NZHS participant's food and physical environments contributed to BMI outcomes. The results of the regression analysis conclude that this research method was unable to find any statistically significant connection between BMI and the participants surrounding environment. Table 5 and 7 suggest there is a minor positive correlation between BMI and the surrounding environment. As the correlation is so minor, it does not suggest a significant trend. Participants that live in areas

with a high number of unhealthy food outlets and low amounts of greenspace are expected to have a higher BMI, due to their exposure to an obesogenic environment. Adversely, participants that live in areas with a low number of unhealthy food outlets and high amounts of greenspace are expected to have lower BMI due to their lack of exposure to obesogenic environments. The results of this research were unable to support these expectations. The number of unhealthy food outlets or amount of greenspace did not significantly influence the BMI of the Hamilton participants.

Similar results were found in the analysis between mode and transport. The results of the regression analysis suggest that participants who bike and skate are exposed to the most greenspace. According to previous studies, this should make these participants more physically active. The nationwide analysis results showed that skate has a lowest mean BMI of the five transport modes sampled. The NZHS skate option did accommodate other forms of active transport. The results of this analysis can suggest that participants that skate are the most physically active, as they have the lowest BMI. Their exposure to greenspace is more significant than the other modes of transport sampled. However, as the r^2 value of skate is very low, there is not enough evidence to suggest that the physical environment is influencing the participants to skate. There were no significant findings in regards to the other modes of transport. One might expect active transport modes to have a higher greenspace exposure than passive transport modes, as greenspace can increase the access and availability of active transport facilities, such as walkways. The results of this analysis did not support this expectation, with really little variation in the R^2 values of active and passive modes of transport. Age and BMI were used as controls in this model. These two variables did not help to improve the statistical significance of the regression model for mode of transport. The connection between BMI and mode of transport were already found to be insignificant based on the results from the nationwide

analysis. BMI made no significant difference to the R squared value when introduced within the regression model. This suggests that participant's food and physical environments in Hamilton did not contribute to mode of transport that participants use. It is important to understand how the food and physical environments can influence mode of transport. A more physically active environment could encourage school children to use active transport to and from school. Many previous studies have referenced the benefits of active transport for school children. The results of this analysis have failed to establish a connection between mode of transport and the food and physical environments of Hamilton school children. Mode of transport was in turn found to have no bearing on BMI status.

The results of the nutrition intake analysis were not statistically significant, due to the low R squared values of the regression model. The R squared value of the regression analysis between fizzy drinks intake and the food environment was the most interesting finding. Despite the R squared value still being low (0.014), this was pointedly higher than the R squared values of takeaway, vegetable and fruit. Of the four nutritional categories sampled, fizzy was represented highest. Over three quarters of Hamilton participants consumed fizzy drinks at least once in the sampled week, more than any of the other three categories. Fizzy drinks have a high sugar content, making them highly unhealthy, yet highly appealing to children. Chapter 4 of this research project referenced the high level of sugar consumption in New Zealand. This finding among Hamilton children is consistent with high sugar consumption. As is mentioned, the R square value between fizzy intake and the food environment is too low to suggest a significant trend. However, in the context of the regression analysis between nutrition intake and the environment of Hamilton participants, fizzy drinks are more significantly represented than the others. BMI and age were once again used as controls in this research. The regression analysis between environment and

nutrition intake found no correlation between participants that eat unhealthy food and an obesogenic environment. A higher consumption of fizzy and takeaways was not connected to participants having a higher BMI, nor the composition of the food and physical environments of participants. The purpose of this analysis was to establish if the food and physical characteristics of a participant's environment influence the nutritional value of their diet. The results indicate no reason to suggest this is the case. Overall, the linear regression modelled used to measure the correlation between the participant's environment and obesity did not produce any statistically significant findings.

Hamilton geospatial results summary

The GIS method used for this research project failed to establish any significant correlation between the food and physical environments of the Hamilton participants and any NZHS variables used to measure obesity exposure. Linear regression analysis models were used to test the correlation between the Hamilton participant's environment and BMI, mode of transport and nutrition intake. The results do not suggest that the surrounding food and physical environments in Hamilton contributed to any of the NZHS variables used within this analysis. This research method measured the environment by the number of unhealthy food outlets and amount of greenspace contained within a participant's home, route and school environment. The environment was defined by euclidean buffer zones, which indicated the participant's exposure area. Obesogenic environments were characterised in this research method as areas with a high number of unhealthy food outlets and low amount of greenspace. This research project expected that school children who were exposed to obesogenic environments (as defined by the research method) were more likely to have a higher BMI. Based on the results of the Hamilton geospatial analysis, this research project can conclude that the surrounding food and physical environments

do not influence BMI levels. School children that live in the obesogenic environments were not shown to have a higher BMI levels than school children from non-obesogenic environments. Obesogenic environments in Hamilton do not contribute to the obesity outcomes of NZHS participants.

7.2 Wide context of Obesogenic Environments

This section will discuss how the findings of this project related to previous research on obesogenic environments. Previous research defining, measuring and creating obesogenic environments was closely reviewed when conceptualizing this research project. The results of this research project will now be discussed in the context of previous findings for obesogenic environment studies.

This research project was not able to find any significant correlation between obesogenic environment exposure and BMI level. This finding is reflected in the majority of previous research attempting to measure the built environment. No major research study to date has managed to identify a significant correlation between obesogenic environments and obesity outcomes. Jones and Britain (2007) has alluded to the large number of different factors that influence the built environment. This makes the built environment difficult to define, and by extension, difficult to measure. This research project measured both the food and physical characteristics of a participant's environment. Previous research reviewed elected to measure either the food or physical environment of the area, but not both. This researcher argues that this approach does not fully account for the imbalance that obesity creates between the food and physical components of our individual's lifestyle. Obesity is defined by an imbalance between energy input and output. This notion is reflected in the exposure to an individual's surrounding environment. The food environment can be understood as the input, and the physical environment can be understood as the output; an imbalance between input and output is the key identifier of an obesogenic

environment. It is therefore necessary to measure both the food and physical environments when measuring an obesogenic environment. This allows for a comparative analysis between these two factors, which accounts for the imbalances which are typically associated with these areas.

Previous research has used a variety of different indicators within a built area to measure the obesogenic environment. This research project measures the food environment by the number of unhealthy food outlets, and the physical environment by the amount of greenspace. Previous literature has advocated unhealthy food outlets and greenspace as strong indicators of unhealthy or healthy environments respectively. These were the only indicators used to define the food and physical environments of the Hamilton participants, which could explain the lack of significant results achieved through the geospatial analysis. Future research into Hamilton (and indeed other New Zealand cities) should consider a wider range of indicators within the food and physical environments. Previous research by Pomerleau *et al.* (2013) suggested measuring aspects of physical access within a participants environment such as walkability, which would provide more substantial evidence when measuring the physical environment.

The biggest limitation to using GIS to measure obesogenic environments is in inability to account for an individual's social environment. Elinder and Jansson (2009) have made note of this, stating the failure to measure the social environment makes it difficult to establish casual relationships between environmental factors and a population's diet. GIS methods are able to model obesogenic environments based on the built environment, but are unable to model how social indicators of behaviour influence how people interact within the built environment. This research project used specific questions for NZHS to determine if certain social indicators of participants influenced their exposure to an obesogenic environment. The NZHS information was intended to help understand how the participants interact within the GIS modelled environment, i.e. how the

participant got to school, how much unhealthy food they eat etc. Ultimately, the social indicators did not provide enough evidence to suggest a correlation between participants BMI the surrounding environment.

The NZHS variables used did not provide a sufficient amount of information to confidently predict behaviour within the environment. This research method measured obesity exposure within the home, route and school environments. The NZHS information did not demonstrate sufficient evidence to suggest how their social behaviour would be connected to environmental exposure. A key example of this was the nutrition intake variables. These variable detail how many times per week a participant consumed fizzy drinks, takeaways, vegetables and fruit. The GIS modelled food environment created by this research project only accounts for the external community food environment. As is mentioned in Chapter 3, there are three food environments in a community; the home, community and school food environment. The NZHS nutritional information does not state where the participant consumed this food, whether it be at home, in the community or at school. The GIS method is unable to account for the social environment and behaviour of the participant. Participant privacy was another barrier to predicting the social environment of the participant. In order to ensure the privacy and safety of participant's information, the routes to school were modelled based on the shortest distance from home to an age and gender appropriate school. There was no way of knowing if this route was accurate, which further limits the ability to account for the participant's social environment.

Ecological indicators in epidemiology are hard to account for. There are a large number of factors that contribute to the health outcomes. Measuring environmental exposure to obesity considers only one of the many different attributes that determine the health outcomes of obesity. The next

section of Chapter 7 will discuss the applications of this research projects key findings to obesity intervention and prevention in New Zealand.

7.3 Future Implications

This section will discuss the future implications of the results of this research project. The results will be discussed in the context of obesity in New Zealand and internationally. The nationwide analysis section provided the most significant findings for this research project. The Hamilton geospatial analysis failed to establish any concrete connections between obesogenic environments and obesity exposure. Hamilton Geospatial results focus on BMI outcomes specifically. The focus of BMI status may be too direct to identify a significant trend. Future research into the obesogenic environment should seek to identify how the environment is influenced by the symptoms of obesity, rather than measuring obesity itself. This research project has described obesity as an imbalance between input and output, which is reflected in an obesogenic environment. Future research should focus more on measuring the inputs and outputs of the food and physical environments that are known to impact obesity. The symptoms that lead to an obesogenic environment are well recognized, such as low walkability, high density of fast food etc. There are too many unknowable facets of the social environment to expect meaningful results when directly measuring obesity indicators such as BMI. Measuring the indirect indicators of obesity would be beneficial for future health research, particularly in regards to obesity intervention. If the symptoms of obesogenic environments are better understood, intervention can help to target the aspects of the built environment that can indirectly impact obesity levels. Previous examples of health interventions have shown that the indirect influence on obesity can still be considered successful. The sugar tax in Mexico discussed in Chapter 4 did not show a drop in childhood obesity, but did experience a noticeable decrease in sugar consumption; this will help to reduce

obesity rates in the long term. Measuring obesity symptoms, rather than obesity itself could help to provide more robust results, and offer suggestions on future built environment obesity intervention.

In the context of New Zealand obesity, the nationwide findings could have important future implications, particularly on obesity intervention. New Zealand Health Minister Johnathan Coleman has stated the need to introduce a health target for obesity reduction in the future. The key findings of this research projects can educate the way in which obesity intervention strategies can be approached in the future. The social indicators found to be significant in this research project (namely ethnicity and social deprivation) should be carefully considered in future intervention strategies. Community examples of obesity prevention programmes such as APPLE and Project Energize are proven to be effective in schools at a regional level. If national obesity rates are to decrease, these prevention programmes need to be introduced at a national level. Ethnicity and social deprivation are significant indicators of obesity in New Zealand. Future intervention strategies should be targeted to reduce the inequalities between these two social indicators. Based on the results for this research project, reducing inequalities between these facets could have a positive influence on both the ethnic and socially deprived minorities, and the overall level of obesity in New Zealand. This research project has already stated obesity is one of the most severe public health issues New Zealand faces in the future. New Zealand currently sits third in the world for obesity rates, (OECD, 2014). The need for intervention has been required, yet thus far has not been implemented. This research recommends that future intervention be done with consideration to bridging the inequalities between the ethnicities and socially deprived demographics shown to experience higher levels of exposure to obesity in New Zealand public health.

7.4 Limitations

There were several key limitations in this research project. The main limitations were the geospatial aspects of the research method, which were clearly outlined in the method section of this research project. The key limitation to the research method were the geospatial assumptions made about the school and route environments of Hamilton participants. As was mentioned in the method, the only geographic information known about the Hamilton participants was the MB they lived in. There was no geospatial information detailing what school the participants attended, nor the route they used to get from home to school. Network analysis was used to estimate the most likely route the participants will take to school. Distance was referenced in a number of previous research studies as an important consideration in network analysis. The participants were therefore sent to nearest school based on distance within the road network. Variables from the NZHS like age and gender allowed the network analysis to ensure participants were sent to a school matching the age and gender. Despite this, there was no way of knowing for certain if the GIS modelled route was actually the route the participant took to school. This research method was forced to make geospatial assumptions about the route and school environments of the school children. This was to ensure that the personal information of the participant remained anonymous.

The route environment was the primary indicator used to map participant exposure to the food and physical environments in Hamilton. The buffer zones around the home, route and school environments were measured for unhealthy food outlets and greenspace, which defined their exposure to obesogenic environments. As the route and school environment of the participants are estimated by network analysis, the food and physical environments exposure areas are therefore also assumptions. NZHS data indicated whether participants were consumed unhealthy food sources, yet as the route environment was GIS modelled there is no way of knowing for

certain if this geospatially modelled food and physical environment was the actual environment the participant was exposed to. The NZHS data is highly confidential, with participants giving personal health information. The privacy and safety was the primary consideration in the application of this research. As a result, the geospatial analysis of the participant's environment was based on assumptions from previous research, making it impossible to know if the GIS modelled routes were accurate.

There were limitations to the NZHS data on mode of transport. This data contained responses from NZHS children aged 5-14, asking what mode of transport they used to get to and from school. Multiple responses were possible for this question, which provided difficulties in the nationwide analysis between mode of transport and BMI. One of the key aims to this research was to establish whether mode of transport contributes to BMI status in NZHS participants. Active transport modes were predicted to have a lower BMI status; vice versa for passive forms of transport. However, as multiple responses were possible, participants used both active and passive modes of transport to and from school. This could have misrepresented the results of the regression analysis between BMI and mode of transport.

There are some important limitations to using buffer zones to measure the participant's food and physical environments. The exposure to the food and physical environment is based on the number of unhealthy food outlets and amount of greenspace in the buffer zones. The buffer zones were created around the data points of the home and predicted school, and the predicted school routes of participants. This research method measures exposure in the context of the journey to and from school. The NZHS variables such as nutrition intake is considered across all aspects of the Hamilton environment, which is not necessarily accounted for by the coverage of an individual's buffer zone. These potential inaccuracies were expected as a limitation in this research project.

7.9 Conclusion

The research aim of this study was to establish a connection between exposure to obesogenic environments and BMI status of NZHS 2013/2014 participants aged 5-14. This research project was based in New Zealand. The current rate of obesity is of major concern, and presents a significant cost to New Zealand public health in the future. The research method was conducted in two parts. Part 1 investigated the connection between BMI and selected responses from NZHS participants, aiming to identify the social indicators that impacted BMI. Part 2 conducted a geospatial analysis between obesogenic environments in Hamilton and BMI outcomes of NZHS participants. NZHS responses such as mode of transport and nutrition intake were also tested against the environment, attempting to identify if the participants environment contributed to these health outcomes.

The results of this research project found little geospatial correlation between obesogenic environments and BMI outcomes. The regression analysis results were not significant enough to suggest a trend exists between these two factors. These results reflect the difficulty of geospatial epidemiology research. Predicting the outcomes of obesity by investigating environmental exposure failed to provide a sufficient amount of evidence that would validate the research aim. Incorporating aspects of a participant's social environment should be an important consideration for future research. The response to obesity is currently a source of debate in New Zealand. Intervention is required if the high rates of obesity are to stabilize in the future. The key threat is posed to New Zealand children, who will continue to be exposed to obesity without meaningful obesity intervention. Although this project failed to establish a geospatial connection between obesogenic environments and obesity outcomes, the social demographic findings should be considered in any obesity intervention strategies in the future of New Zealand public health.

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Appendix

8.1 Appendix 1: BMI chart

Body Mass Index (BMI) Chart for Adults																																									
		Obese (>30)										Overweight (25-30)										Normal (18.5-25)										Underweight (<18.5)									
		HEIGHT in feet/inches and centimeters																																							
WEIGHT		4'8"	4'9"	4'10"	4'11"	5'0"	5'1"	5'2"	5'3"	5'4"	5'5"	5'6"	5'7"	5'8"	5'9"	5'10"	5'11"	6'0"	6'1"	6'2"	6'3"	6'4"	6'5"																		
lbs (kg)		142cm	147	150	152	155	157	160	163	165	168	170	173	175	178	180	183	185	188	191	193	196																			
260	(117.9)	58	56	54	53	51	49	48	46	45	43	42	41	40	38	37	36	35	34	33	32	32	31																		
255	(115.7)	57	55	53	51	50	48	47	45	44	42	41	40	39	38	37	36	35	34	33	32	31	30																		
250	(113.4)	56	54	52	50	49	47	46	44	43	42	40	39	38	37	36	35	34	33	32	31	30	30																		
245	(111.1)	55	53	51	49	48	46	45	43	42	41	40	38	37	36	35	34	33	32	31	31	30	29																		
240	(108.9)	54	52	50	48	47	45	44	43	41	40	39	38	36	35	34	33	33	32	31	30	29	28																		
235	(106.6)	53	51	49	47	46	44	43	42	40	39	38	37	36	35	34	33	32	31	30	29	29	28																		
230	(104.3)	52	50	48	46	45	43	42	41	39	38	37	36	35	34	33	32	31	30	30	29	28	27																		
225	(102.1)	50	49	47	45	44	43	41	40	39	37	36	35	34	33	32	31	31	30	29	28	27	26																		
220	(99.8)	49	48	46	44	43	42	40	39	38	37	36	34	33	32	32	31	30	29	28	27	26	25																		
215	(97.5)	48	47	45	43	42	41	39	38	37	36	35	34	33	32	31	30	29	28	28	27	26	25																		
210	(95.3)	47	45	44	42	41	40	38	37	36	35	34	33	32	31	30	29	28	28	27	26	25	24																		
205	(93.0)	46	44	43	41	40	39	37	36	35	34	33	32	31	30	29	29	28	27	26	26	25	24																		
200	(90.7)	45	43	42	40	39	38	37	35	34	33	32	31	30	30	29	28	27	26	26	25	24	23																		
195	(88.5)	44	42	41	39	38	37	36	35	33	32	31	31	30	29	28	27	26	26	25	24	24	23																		
190	(86.2)	43	41	40	38	37	36	35	34	33	32	31	30	29	28	27	26	26	25	24	24	23	22																		
185	(83.9)	41	40	39	37	36	35	34	33	32	31	30	29	28	27	27	26	25	24	24	23	22	21																		
180	(81.6)	40	39	38	36	35	34	33	32	31	30	29	28	27	27	26	25	24	24	23	22	22	21																		
175	(79.4)	39	38	37	35	34	33	32	31	30	29	28	27	27	26	25	24	24	23	22	22	21	20																		
170	(77.1)	38	37	36	34	33	32	31	30	29	28	27	27	26	25	24	24	23	22	22	21	21	20																		
165	(74.8)	37	36	34	33	32	31	30	29	28	27	27	26	25	24	24	23	22	22	21	21	20	20																		
160	(72.6)	36	35	33	32	31	30	29	28	27	27	26	25	24	24	23	22	22	21	21	20	19	19																		
155	(70.3)	35	34	32	31	30	29	28	27	27	26	25	24	24	23	22	22	21	20	20	19	18	18																		
150	(68.0)	34	32	31	30	29	28	27	27	26	25	24	23	23	22	22	21	20	20	19	19	18	18																		
145	(65.8)	33	31	30	29	28	27	27	26	25	24	23	23	22	21	21	20	20	19	19	18	18	17																		
140	(63.5)	31	30	29	28	27	26	26	25	24	23	23	22	21	21	20	20	19	18	18	17	17	16																		
135	(61.2)	30	29	28	27	26	26	25	24	23	22	22	21	21	20	19	19	18	18	17	17	16	16																		
130	(59.0)	29	28	27	26	25	25	24	23	22	22	21	20	20	19	19	18	18	17	17	16	16	15																		
125	(56.7)	28	27	26	25	24	24	23	22	21	21	20	20	19	18	18	17	17	16	16	16	15	15																		
120	(54.4)	27	26	25	24	23	23	22	21	21	20	19	19	18	18	17	17	16	16	15	15	15	14																		
115	(52.2)	26	25	24	23	22	22	21	20	20	19	19	18	17	17	16	16	16	15	15	14	14	14																		
110	(49.9)	25	24	23	22	21	21	20	19	19	18	18	17	17	16	16	15	15	15	14	14	13	13																		
105	(47.6)	24	23	22	21	21	20	19	19	18	17	17	16	16	15	15	14	14	14	13	13	13	12																		
100	(45.4)	22	22	21	20	20	19	18	18	17	17	16	16	15	15	14	14	14	13	13	12	12	12																		
95	(43.1)	21	21	20	19	19	18	17	17	16	16	15	15	14	14	14	13	13	13	12	12	12	11																		
90	(40.8)	20	19	19	18	18	17	16	16	15	15	15	14	14	13	13	13	12	12	12	11	11	11																		
85	(38.6)	19	18	18	17	17	16	16	15	15	14	14	13	13	13	12	12	12	11	11	11	10	10																		
80	(36.3)	18	17	17	16	16	15	15	14	14	13	13	13	12	12	11	11	11	11	10	10	10	9																		

8.2 Appendix 2: List of Hamilton Schools

NAME	REGION	DECILE
Aberdeen School	Hamilton	7
Bankwood School	Hamilton	5
Berkley Normal Middle School	Hamilton	9
Crawshaw School	Hamilton	1
Deanwell School	Hamilton	4
Fairfield College	Hamilton	3
Fairfield Primary School	Hamilton	1
Forest Lake School	Hamilton	3
Frankton School	Hamilton	3
Glenview School (Hamilton)	Hamilton	8
Hamilton Boys' High School	Hamilton	7
Hamilton East School	Hamilton	4
Hamilton Girls' High School	Hamilton	7
Hamilton West School	Hamilton	6
Hamilton's Fraser High School	Hamilton	4
Hillcrest High School	Hamilton	9
Hillcrest Normal School	Hamilton	10
Hukanui School	Hamilton	10
Insoll Avenue School	Hamilton	1
Knighton Normal School	Hamilton	5
Maeroa Intermediate	Hamilton	4
Marian Catholic School (Hamilton)	Hamilton	8
Melville High School	Hamilton	4
Melville Intermediate	Hamilton	4
Melville Primary School	Hamilton	3
Nawton School	Hamilton	2
Peachgrove Intermediate	Hamilton	5
Pukete School	Hamilton	8
Rhode Street School	Hamilton	1
Sacred Heart Girls' College (Ham)	Hamilton	7
Silverdale Normal School	Hamilton	8
South City Christian School	Hamilton	6
Southwell School	Hamilton	10
St Andrew's Middle School (Hamilton)	Hamilton	6
St Columba's Catholic School (Frankton)	Hamilton	5
St John's College (Hillcrest)	Hamilton	7
St Joseph's Catholic School (Fairfield)	Hamilton	7
St Paul's Collegiate (Hamilton)	Hamilton	10

St Peter Chanel Catholic Sch (Te Rapa)	Hamilton	8
St Pius X Catholic School (Melville)	Hamilton	3
Te Kura Kaupapa Maori O Te Ara Rima	Hamilton	1
Te Rapa School	Hamilton	6
TKKM O Toku Mapihi Maurea	Hamilton	3
Vardon School	Hamilton	5
Waikato Diocesan School For Girls	Hamilton	10
Waikato Diocesan School For Girls	Hamilton	10
Whitiora School	Hamilton	2
Woodstock School	Hamilton	5